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CORPORATE SCIENCE, INNOVATION AND FIRM VALUE

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Corporate Science, Innovation and Firm Value

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Abstract

It can be observed that many R&D performing firms produce scientific knowledge and disclose research outcomes in scientific journals. At the micro-level, prior work identified several potential benefits of such a strategy like superior access to informal information networks or the opportunity of recruiting the best PhD graduates. However, scientific research is costly and subject to considerable uncertainty with respect to the outcomes, and the disclosure may lead to spillover effects that decrease the ability of firms to generate returns of their R&D investments. Overall, it remains unclear if and under what conditions science-oriented strategies are beneficial for firms. We address this gap and examine the impact of scientific activities on the firm's market value using accounting data for US firms from Compustat and matched patent and scientific publication data. We find evidence for a positive impact of scientific publication stocks on the firm value beyond the effects of R&D, patent stocks and patent quality.

Keywords: R&D, Industrial science, Market value, Tobin's Q, Knowledge disclosure, Econometric evidence

JEL classification: G32, O31, O34

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1 Introduction

The effect of Research and Development (R&D) activities on firm performance is an interesting question both for innovation scholars and managers and consequently received considerable attention in the innovation literature. One way to assess the performance effects of R&D is using a market-value approach, which has the convenient property that no assumptions are required about the time-lags between knowledge creation and the financial returns since the financial markets immediately respond to new information. Moreover, such an approach also allows for insights to managers since it is an important question how the stock market reacts to the firm's investment decisions. Acknowledging the relevance, many scholars have addressed the relationship between knowledge assets and a firm's market value (e.g. Griliches, 1981; Jaffe, 1986; Griliches and Cockburn, 1988; Hall, 1993; Blundell et al., 1999; Bloom and van Reenen, 2002; Toivanen et al., 2002; Hall et al., 2005; Nesta and Saviotti, 2006; Hall et al., 2007; Ceccagnoli, 2009). In the vast majority of these studies, knowledge assets have been operationalized by R&D investments and patents. The typical and quite consistent findings reveal a positive effect of R&D activities on the market valuation of firms, and inventive outcomes as well as quality indicators of inventive outcomes are found to generate a premium for it.

Beyond the consideration of R&D investments, patent counts and patent quality, there have only been a few attempts that considered the heterogeneity of firm knowledge and strategies as determinants of the market value of firms. More specifically, there is only very limited empirical evidence on the performance effects if firms are engaged in boundary-spanning activities. One relevant expression of boundary-spanning is the engagement of firms in the production of scientific knowledge and the voluntary dissemination of research results, which is a core practice in "Open Science" but appears counterintuitive in a corporate context (see Dasgupta and David, 1994; Alexy et al., 2013). A better understanding of the corresponding firm performance effects is informative not only for innovation scholars but especially for managers in firms that face the question whether and to what extent they should adopt academic practices. It is not clear if more science-oriented firms get rewarded for their innovation strategies. To our best knowledge, the study of Deng et al. (1999) is the only one which explicitly considers scientific research in firms as a determinant of the firm value. However, the authors did not consider explicit contributions of firms to the stock of scientific knowledge. We address this gap in the literature by examining the role of scientific activities on the "Tobin Q" valuation of firms. In this respect, we aim to distinguish the impact of scientific activities between the effects that derive from the created knowledge itself (basic research outcomes) and effects that are based on the voluntary disclosure of the research results.

The starting point of our research interest is the observation that many R&D performing firms do not only rely on scientific information as a source for their innovation activities but are also active contributors to the stock of scientific knowledge (Hicks, 1995; Stephan, 1996; Simeth and Raffo, 2013). Although basic research potentially allows for creating highly innovative outcomes that are of a high commercial value, it is also more uncertain regarding the achievable outcomes, costly in its execution and more difficult to appropriate (Nelson, 1959; Rosenberg, 1990; Aghion et al., 2008). Apart from the underlying research, the disclosure of research findings in the form of scientific publications is recognized as a signalling and appropriation device. Firms may target multiple stakeholder groups like academic scientists or professional customer groups which are potentially responsive to the disclosure of knowledge (Hicks, 1995; Stern, 2004; Penin, 2007; Polidoro and Theeke, 2012). However, disclosure implies additional costs due to potential knowledge spillovers, incentive schemes for scientists that reward publication success, the need for loyalty strategies to keep successful and visible firm scientists, and opportunity costs based on the necessity to codify the knowledge in a structured format (Cockburn et al., 1999; Kinney et al., 2004; Liu and Stuart, 2010).

Our empirical analysis relies on firm-level information from the US Compustat edition and matched scientific publication and patent data for a sample of 1,509 firms (7,022 firm-year observations) from sectors that are classified as "High-Tech" as defined by the OECD definition. The results of our econometric analysis suggest a positive relationship between scientific publication stocks of firms and their Tobin Q valuation. In this respect, there is some indication that the firm openness matters beyond the achievements of scientific outcomes. The positive impact of scientific publication stocks holds in the presence of variables that capture the extent of R&D activities, patent stocks, and patent quality. However, we also found some heterogeneity of the effect depending on sectors and firm size.

The remainder of this paper is organized as follows: In Section 2, we provide a brief and non-exhaustive review of the most important studies that examine the impact of knowledge assets on firm value. In Section 3, we discuss the mechanism why scientific research in firms and the voluntary disclosure of results may impact the market valuation. We present data, variables and the econometric design in Section 4, before we show and discuss our results in Section 5. We conclude in Section 6.

2 Knowledge assets and stock market valuation

Based on its high relevance, the relationship between knowledge assets and firm value has received considerable attention by innovation scholars.[1] Early work (e.g. Griliches, 1981; Jaffe, 1986; Connolly and Hirschey, 1988; Hall, 1993) measured knowledge assets by R&D stocks and the quantity of inventive outcomes as reflected by patent stocks. More recent studies built on this work and accounted for the expected commercial value of patents by adding quality indicators that are based on forward citation counts or patent family size (Lanjouw and Schankermann, 2004; Hall et al., 2005; Hall and Oriani, 2006; Hall et al., 2007). These studies are widely consistent in documenting a positive effect of R&D and patent stocks on Tobin's Q. Moreover, patent quality indicators reveal a premium on the

[1] In Appendix A.1, we provide an overview about the most important studies.

stock market valuation which is in line with the observation that the value of patents is highly skewed and only a minor share of all patents is of a high commercial value (Hall et al., 2005). With respect to the econometric estimation strategy, knowledge assets are typically regarded as additive to the amount of tangible firm assets ("hedonic model").

Complementary studies analyse the relationship between knowledge assets and firm valuation with special attention to environmental factors, moderating influences and specific sector contexts. Using information from the Yale and Carnegie Mellon surveys about the effectiveness of various channels of knowledge protection, Cockburn and Griliches (1998) as well as Ceccagnoli (2009) found that knowledge assets are valued higher if patents are considered as important protection instrument. Indirectly, this result indicates that not only the achievement of inventive outcomes provides a valuable signal, but also that the legal patent right is perceived as valuable by the stock market. In related work with respect to these two studies, McGahan and Silverman (2006) show that incoming spillovers from competitors lead to higher market values of firms. Furthermore, recent work analysed the relationship between knowledge assets and market value specifically for the software (Noel and Schankerman, 2009; Hall and MacGarvie, 2010) and biotechnology sectors (Decarolis and Deeds, 1999; Nesta and Saviotti, 2007). While biotechnology is a sector where formal intellectual property has traditionally had a strong role for appropriation, the studies on software are particularly motivated by the recent legislative changes in the patentability of software.

Of particular relevance for our work is the study by Deng et al. (1999) which is to our best knowledge the only study that investigates the impact of scientific research in firms on their market value. More specifically, Deng et al. (1999) examine whether science-based patents lead to an effect on the market valuation beyond the standard measures of R&D and patent stocks. The authors documented a positive effect, which indirectly indicates that (basic) research leads to more successful innovations. However, the authors do not analyse the role of voluntary scientific contributions and only rely on a patent-based measure. In the following Section, we discuss the reasons why observable scientific contributions may have an impact on the market value of firms.

3 Scientific research, publications and firm value

From a conceptual point of view, one can distinguish between positive effects that are based on the creation of a scientific knowledge stock, and the active and voluntary disclosure of the corresponding knowledge. In Table 1, the potential mechanisms are summarized:

-- Insert Table 1 here --

To begin with the first dimension, firms engaging in fundamental research are regarded as being more capable of re-combining technologically distant knowledge and creating more valuable innovations than other firms (Nelson, 1959; Rosenberg, 1990). Firms with (basic) research capacities typically have superior capabilities to understand and integrate external knowledge and to identify promising trajectories for applied research and development (Cohen and Levinthal, 1989; Fleming and Sorenson, 2004). Corresponding empirical research shows that internal and external knowledge is complementary particularly when firms invests into basic research, leading to superior inventive outcomes (Cockburn and Henderson, 1998; Gittelman and Kogut, 2003; Lim, 2004; Cassiman and Veugelers, 2006; Fabrizio, 2009). Moreover, firms that are engaged in basic research develop inventions at a faster pace which may allow for realizing first mover advantages (Rosenberg, 1990; Fabrizio, 2009). However, the execution of basic research often requires specific human resource compositions and incentive systems (see Cockburn et al., 1999), and the research is subject to higher uncertainty (Nelson, 1959; Rosenberg, 1990). Despite these costs, overall we expect a positive impact of basic research on firm value.

Beyond the aspect that scientific outcomes reflect the engagement of firms in basic research, the *disclosure* of research results may impact firm performance and the expectations of the firm's shareholders via different channels. With respect to external knowledge flows it has to be considered that inflows are at least partially not exogenous but need to be established explicitly. While academic knowledge codified in scientific journals can be accessed without notable constraints, academic scientists might be reluctant to interact directly with firms. In order to accept formal collaborations or maintain informal contacts with firm scientists, academic researchers may require credible signs that an interaction is valuable with regard to the research topics and that the firm respects academic disclosure principles (Hicks, 1995; Cockburn and Henderson, 1998; Simeth and Raffo, 2013). In practical terms, companies could have an advantage in accessing external knowledge if they actively contribute to the scientific knowledge stock by publishing in scientific journals. A related aspect is the use of scientific publications as an instrument to attract highly-qualified university graduates that are required for the execution of R&D. Particularly those graduates with strong research-capabilities may have an interest in participating in publication activities and select into firms which offer corresponding possibilities (Stern, 2004; Sauermann and Roach, 2013).

Apart from these rather indirect signals that indicate the capabilities of firms to access external knowledge and researchers, the disclosure of research outcomes could have a direct informational value to the financial markets. The successful execution of R&D, and particularly basic research, can be highly uncertain with respect to the success and commercial potential of the envisaged inventions. Scientific publications may reflect promising intermediate research outcomes and reduce the uncertainty about the success of the R&D program with respect to future inventions. In a linear timeline, scientific publications can potentially provide information between R&D investment decisions as an input factor and the realized inventions represented by patents and products. Alternatively, in cases where patents and publications derive from one single research project (see Murray, 2002; Murray and Stern, 2007), publications may offer additional information with respect to the quality and the novelty of the research outcomes and therefore act as a valuable sign that the corresponding patent application will get granted. Since scientific journals demand novelty (Meyer and Bhattacharya, 2004), a successful publication may indicate that the novelty requirement of the patent application is fulfilled, and therefore signal that a positive examiner feedback can be expected. As opposed to the European Union where the patent application has to be filed first to fulfil the novelty requirement, in the United States the scientific equivalent can be published 12 months before the patent application.[2] Therefore, such a potential signalling impact of publications is even stronger in the US context than in the European one.

Another direct cause-effect relationship refers to the use of scientific publications as an appropriability device. Scientific publications may encourage the adoption of science-based products such as medical drugs or scientific and medical instruments (Polidoro and Theeke, 2012). These products are sold to professional customer groups or through intermediaries (university hospitals or clinicians) that need to know the technological properties of the product. In this respect, disclosure in scientific peer-reviewed journals can act as certification that establishes credibility among the professional customers. Another use of scientific documents can lie in hampering the activities of competitors by establishing prior art (De Fraja, 1993; Parchomovsky, 2000; Della Malva and Hussinger, 2012). Companies can establish prior art by publishing, and the disclosed outcomes cannot be patented anymore by competing firms working on the same inventions.

However, there are also costs associated with the publication process which could outweigh the benefits. The most obvious aspect is undesired spillover effects which allow the competitors to benefit from the voluntary knowledge disclosure (Arrow, 1962). The knowledge flows may reduce the cost of imitation for competitors or facilitate invent-around possibilities of patented knowledge. Moreover, the publication process itself can lead to opportunity costs since the firm's researchers have to prepare the documents to fulfil the respective journal requirements, to interact with referees or to codify knowledge that could have remained tacit (see Kinney et al., 2004). In addition, firm scientists that achieve to publish are more visible to other potential employers, which may impose the need for retention strategies (see Liu and Stuart, 2010; Kim and Marschke, 2005). Nevertheless, based on the variety of signalling possibilities, we expect a positive impact of scientific disclosure on firms' market value.

[2] One has to keep in mind that the usual time lags between first submission and acceptance are much shorter in many academic disciplines than in economics or management research, which makes it likely that the scientific equivalent is published before the patent gets granted under the assumption that the corresponding publication is not submitted much later than the patent application.

4 Methodology

4.1 Data sources

The analysis is based on a sample of large US-American firms from high-technology sectors as defined by the OECD. More specifically, we considered the sectors of pharmaceuticals and biotechnology, telecommunication equipment and semiconductors, aircraft, and scientific and medical instruments. Additionally, we included the chemicals sector since it is often recognized as a science-oriented sector. These sectors represent a natural setting for our study since they are known to draw from scientific knowledge as input factor and show variation in their publication outputs (see Simeth and Raffo, 2013). Our dataset covers the time period of 1996-2003 and firms were included in the sample based upon the criterion that they invested in R&D at least in one year during this period.[3] The firm-level information comes from the Compustat US edition, the patent data from EPO PatStat (which includes the entire USPTO collection), and the publication data from Elsevier's Scopus database.

The matching process of firm-level data with publication and patent information deserves further discussion since name-based matching procedures are potentially subject to errors.[4] To achieve high-recall rates of the publication and patent numbers, we carefully pre-cleaned all firm names by correcting misspellings and removing legal firm identifiers ("Inc.", "Corp."). The technical implementation of the publication and patent matching process differed in the sense that scientific publications were retrieved manually from the Scopus online database whereas the patent data was matched using an offline source. The former leads to a more time-consuming gathering process than the "automatic" offline matching, while the latter requires an extensive manual cleaning of the algorithm-based matching results. The manual retrieval from Scopus allowed for a direct inspection of the hits including an immediate exclusion of incorrect affiliations that are based on institutions with an identical name component.

The offline-matching procedure with patent data from the EPO Patstat database required specific steps. First, all names were pre-tested online in the EPO Espacenet search module to detect problematic names. Subsequently, firms with ambiguous names were either excluded directly or marked for a detailed manual inspection once the actual matching was executed. Second, after pre-testing several matching algorithms, we identified a powerful algorithm that achieves a high recall rate while simultaneously limiting false positive hits (see Raffo and Lhuillery, 2009). Afterwards, the resulting matches were checked manually with particular focus on firms with atypical input-output

[3] The period of analysis is determined by data availability constraints, since SCOPUS extended its journal coverage considerably in the year 1996, potentially inducing bias to the econometric estimations. See *http://www.info.sciverse.com/UserFiles/2508.SciVerse.Scopus_Facts_Figures%28LR%29.pdf.*

[4] See Thoma et al. (2010) for a general discussion on the matching process of firm-level data with other sources.

ratios and those that have been identified in the pre-tests as being problematic.[5] In order to provide further evidence on the quality of our patent matching process, we also matched our data with the Compustat-NBER dataset by Bessen (2009). We performed regressions with the patent numbers based on our matching and the Compustat-NBER matching (see Appendix A.2), and the results are fully consistent with almost identical coefficients. Since the Compustat-NBER dataset also considers statically the ownership structure for one period, this exercise can additionally establish confidence that our results are not affected by the non-consideration of affiliates in our study.[6]

To avoid biases that origin from Merger &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 book value changes were identified based on the criteria of an increase of more than 300% or decrease of 75% between two subsequent years (see also Griliches, 1981; Hall and Oriani, 2006; Aldieri and Cincera, 2009). We only dropped the firm-year observation where a large change occurred and treated the firm in the years after the event as a new firm (see Griliches and Mairesse, 1984). Excluding them entirely could have led to a selection bias since M&A activities are presumably often based on successful R&D operations and achieved knowledge outcomes given that our sample only includes firms from high-technology sectors. In addition, we excluded the top 1% of firm-year observations with the highest Tobin Q values. To address potential measurement errors and inaccurate initial knowledge stock computations, we additionally dropped observations with extremely high (top 1%) knowledge stock/asset ratios.[7] Finally, we excluded firms with an R&D/Sales ratio higher than 1 and firms with less than 10 employees. Based on these filters, the available sample size for our regression analysis decreased from 10,139 to 7,022 firm-year observations.[8] All financial amounts used were adjusted for inflation using the Gross-Domestic Product (GDP) deflator.

4.2 Variables

To construct our dependent variable, we follow prior work and used the standard "Tobin Q" indicator which represents the ratio of the firm's market value over book value. The market value is composed of the market value of the equity plus the market value of the debts. The first is calculated by the number of outstanding shares multiplied by the stock price at the end of the fiscal year whereas the

[5] A direct download from *EPO Espacenet* was not feasible due to the limited export functions.

[6] An ideal approach would be to consider the affiliation structure of firms in a dynamic manner, i.e. to consider yearly updates (see Czarnitzki et al. 2013, for a recent application). However, this is hardly feasible in our case from a practical viewpoint given the large sample used in our study.

[7] The three measures concerned are R&D/A, PAT/A, PUB/A which are explained in detail in the next section.

[8] See Appendices A.3 and A.4 for details on the impact of the filters on the observation numbers and the sample composition.

market value of debts is approximated with the book value of liabilities (see Blundell et al., 1999; Hall and Oriani, 2006, Ceccagnoli, 2009). The firm's book value is represented by its total assets at the end of the fiscal year.

With respect to the independent variables, we computed several indicators in order to represent the firm's knowledge stocks and their heterogeneity. A core measure is the firm's R&D stock which reflects the overall investment into knowledge production and potential future returns. Since knowledge gets obsolete over time due to the on-going technological development and reactions by competing firms, we applied the frequently used perpetual inventory method assuming the usual 15% depreciation rate for our main models (see e.g. Griliches and Mairesse, 1984; Hall et al., 2005).[9] Therefore, the R&D stock as well as the other knowledge stock indicators explained below are computed as follows:

$$R\&D\ STOCK_t = R\&D_t + (1-\delta)R\&D\ STOCK_{t-1} \tag{1a}$$

Although the computation of the R&D stocks is basically straightforward, one has to make assumptions about the initial R&D stock ($R\&D\ STOCK_{to}$) which remains unobserved. In our study, we applied a standardized growth rate for R&D and the other knowledge stock measures of 8% (Hall and Oriani, 2006; Hall et al., 2007).[10] The initial unobserved R&D stock is approximated as follows:[11]

$$R\&D\ STOCK_{to} = R\&D_{t0}\,/(\delta + g) \tag{1b}$$

The other measures discussed below are accordingly constructed as stocks. Our core interest in this paper lies in the impact of voluntary scientific contributions of firms on their market value. To assess the potential informational value of scientific contributions and their heterogeneity, we construct three measures. First, we capture the amount of scientific contributions by computing a stock measure based on the number of scientific papers published by the firm (*PUB*). To consider the heterogeneity of scientific contributions, we introduce a second measure that reflects their academic quality (*TOPPUB*). If firms are able to publish in leading journals, the scientific quality and originality

[9] We tested also alternative depreciation rates, see Section 5.3.

[10] As an alternative, we computed firm-specific initial stocks using a combination of firm-level and industry-level growth rates. However, this approach leads partly to extreme values and an extrapolation imposes additional assumptions about the persistence of trends, particularly with respect to the additional patent and publication indicators.

[11] This applies specifically to firms that do not have a long pre-sample record in Compustat, whereas the stocks can be (at least partly) computed with observed values for firms with IPO's before 1996.

can be expected to be higher, which may have commercial implications in the long term. Moreover, publishing in leading journals less likely reflects appropriation motives since the publication process is riskier with higher likelihoods of rejections and potential delays imposed by referee requests for further experiments or documentation. Since our sample period contains relatively recent years and our data does not include information about the exact citation year, citation analysis cannot be applied due to corresponding data truncation problems. Instead, we used information about journal quality. Since the absolute journal impact depends on the field size and journal impact factors are not completely adjusted, we identify the best journals by five meta-disciplines (Life Sciences, Physical Sciences and Engineering, Social Sciences, Health Sciences and General) and take the top 10% of the journals based on the impact factors within these disciplines. The computed stock variable considers those scientific publications that belong to these top-journals. Similarly, we account for academic co-authorship by identifying the publications that are co-authored publications with academic institutions (*ACADPUB*). This measure captures the degree of connectedness to the scientific community and indicates indirectly the knowledge sourcing capabilities of firms with respect to academic knowledge (Cockburn and Henderson, 1998).

Concerning the firm's inventions, we include several measures that reflect the amount of inventive outputs, their scientific orientation, quality and scope. The absolute amount of inventive outcomes is represented by patent stocks (*PAT*). This measure captures the overall dimension of a firm's inventive activities but does not reflect any heterogeneity in the inventive output. A core measure is the science orientation of the firm's patents in order to represent the importance of scientific information for the firm's inventive activities, the basicness of R&D and the potential to create scientific publications. To proxy the science orientation, we assume that the existence of a scientific document in the backward references of the firm's patents indicates a science-based patent (see also Deng et al., 1999; Della Malva and Hussinger, 2012; Chatterji and Fabrizio, 2012). We were able to identify scientific documents in the Non-Patent-Literature (NPL) section of the patents' backward references using specific keywords and character combinations that have been collected through an extensive screening of the NPL information in the EPO PatStat database. Subsequently, we built a separate stock of these science-based patents (*SCIPAT*). We believe that the *SCIPAT* variable allows to some extent for a differentiation between the research orientation (as opposed to development) and disclosure effects, since it points to basic research outcomes of firms but does not depend on the observation of a scientific contribution in the form of a journal publication. Moreover, the quality of the inventive outcomes (*FWDCIT*) is measured using forward citation counts (Hall et al. 2005). Patents are highly skewed in their technological and commercial value which imposes the need to consider their quality. To deal with the truncation problem of citation counts, we counted only those citations that occur within a five-year window after the priority date of our focal patents (Lanjouw and Schankerman, 2004; Marco, 2007). Finally, we control for the scope of inventive outcomes which reflects the boundaries of the desired patent protection, which is a count variable that is likewise introduced as a stock (*CLAIMS*). A broader protection can increase the likelihood that competing firms are negatively affected in their freedom to operate. As a result, an increasing scope should be positively associated with patent quality and is measured by the number of claims in the patent grant publication (Lanjouw and Schankerman, 2004).

Finally, we control for firm size using the amount of sales (Hall and Oriani, 2006; Belenzon, 2011) and include sector and year dummy variables into our models to account for heterogeneous market valuations across industries and time (see Cockburn and Griliches, 1988; Nesta and Saviotti, 2006; Hall et al., 2005).

4.3 Model and estimation techniques

In this paper, we analyse the relative market value of firms (Tobin's Q) as a function of their knowledge stocks. Following our theoretical discussion, we separate the knowledge of firms into R&D, patent, and publication 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 additive ("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 the firm's assets, and the parameter γ allows for a different valuation of knowledge assets in comparison to the physical assets. The valuation coefficient q_{it} may vary across time, industries and also contains a firm-specific component. The factor σ represents scale effects and is assumed to equal 1 (e.g. Hall et al., 2005).[12] Taking logarithms on both sides and moving tangible assets to the left hand side of the equation yields the following expression:

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

As mentioned above, the knowledge of the firm are measured using R&D investment, patent and scientific publication stocks. To examine whether these stocks impact the market valuations, we introduced correspondingly our variables as ratios of accumulated knowledge over physical assets into the model, which is formalized in equation (4). From a theoretical point of view, R&D, patent and

[12] We tested formally for scale effects by regressing log (Market value) on log (Assets) and industry/time controls, and the coefficient on log (Assets) is 0.98, supporting the assumption of constant scale effects.

publication stocks likely represent different stages of knowledge transformations since R&D investments and codified R&D outcomes in the form of a patent or publication do not likely refer to the same period. Moreover, scientific and inventive outcomes may not only derive from the firm's R&D investments but also through interactions with the environment, which are not necessarily based on financial resource provisions (see the literature on "Open Innovation"). These considerations call for including R&D, scientific and patent knowledge stocks independently into the equations and relating them to the size of the physical assets. An alternative approach to model scientific and inventive outcomes would be to introduce them as stocks denominated by R&D stocks, resulting in an outcome productivity measure (e.g. Hall et al., 2005; Hall and Oriani, 2006; Hall et al., 2007).[13] In order to allow for comparisons with earlier studies and acknowledging this alternative possibility to model knowledge stocks, we performed comprehensive robustness tests (see Table 7). The regression results remain fully consistent with our findings once outliers are removed by adjusting the filters to exclude excessive PUB/R&D and PAT/R&D ratios.

$$\mathrm{Log}\left(\frac{V_{it}}{A_{it}}\right) = \log Q = \log q_{it} + \log\left(1 + \gamma_1 \frac{RD_{it}}{A_{it}} + \gamma_2 \frac{PAT_{it}}{A_{it}} + \gamma_3 \frac{PUB_{it}}{A_{it}}\right) + e_{it} \tag{4}$$

In the empirical setting, *R&D*, *PAT* and *PUB* represent the respective stock measures that have been computed using the perpetual inventory method with an assumed depreciation rate of 15%. In addition, we are interested in capturing the nature of a firm's knowledge stocks in a more detailed way and aim to differentiate between the research orientation and direct disclosure effects, which requires further measures. To detect if these additional variables lead to a different market valuation given the presence of the knowledge stocks of equation (4), we introduced them as ratios that are orthogonal to the main variables. Consequently, the extended model to equation (4) can be written as:

$$Log\left(\frac{V_{it}}{A_{it}}\right) = \log Q = \log q_t + \log\Big(1 + \gamma_1 \frac{RD_{it}}{A_{it}} + \gamma_2 \frac{PAT_{it}}{A_{it}} + \gamma_3 \frac{PUB_{it}}{A_{it}} + \gamma_4 \frac{SCIPAT_{it}}{PAT_{it}} + $$
$$+ \gamma_5 \frac{FWDCIT_{it}}{PAT_{it}} + \gamma_6 \frac{CLAIMS_{it}}{PAT_{it}} + \gamma_7 \frac{TOPPUB_{it}}{PUB_{it}} + \gamma_8 \frac{ACADPUB_{it}}{PUB_{it}}\Big) + e_{it} \tag{5}$$

[13] Under the assumption that scientific publications and patent represent the same knowledge pieces (see literature on Patent-Paper Pairs, e.g. Murray, 2002), scientific publication stocks could also be modelled orthogonally to patents: $\mathrm{Log}\left(\frac{V_{it}}{A_{it}}\right) = \log Q = \log q_{it} + \log\left(1 + \gamma_1 \frac{RD_{it}}{A_{it}} + \gamma_2 \frac{PAT_{it}}{RD_{it}} + \gamma_3 \frac{PUB_{it}}{PAT_{it}}\right) + e_{it}$. Such estimation implies to run the estimations on a sample of patenting firms only. From a theoretical viewpoint, a strong knowledge overlap is a rather strong assumption in the absence of systematic empirical evidence on the nature of published and patented outcomes in the private domain. Moreover, one has also to consider the heterogeneity in the propensity to patent not only between but also within sectors. Nevertheless, we report a corresponding robustness test in Table 7.

As explained in the preceding Section, these measures reflect the science orientation of the firm's patents (*SCIPAT/PAT*), their quality (*FWDCIT/PAT*) and the scope of the desired protection (*CLAIMS/PAT*). With respect to scientific outcomes, information about the academic quality of the scientific output (*TOPPUB/PUB*) as well as the involvement of academic institutions in the creation of the scientific output is of interest (*ACADPUB/PUB*).

Whereas equations (4) and (5) can be directly estimated using Non-Linear Least Squares (NLLS), an approximation with log (1+x) ~ x may allow for applying standard OLS as well as techniques that take the panel structure of our data explicitly into account. Since the approximation quality depends on the realized values of the independent variables, we tested it explicitly and detected a bias of around 10% at the mean values of our knowledge measures. This makes us believe that the approximation can be used while acknowledging that the reported magnitudes are only of limited precision in the light of the additive market value function.[14] The linearization of the market value function implies including the knowledge stock variables as log-level specifications into the regression models (see Hirsch and Seaks 1993 for an explicit discussion). Therefore, all knowledge stocks variables are included correspondingly.

A further econometric concern is related to the potential presence of unobserved firm-specific effects. Surprisingly, this aspect received little attention in the studies which deal with market value estimations (see Griliches, 1981; Jaffe, 1986; Blundell et al., 1999 for exceptions). The standard specification tests on the linear models suggest that OLS and Random Effect models are inconsistent. Therefore, there is a reason for relying on estimation procedures that take firm-fixed effects into account. However, this is not straightforward in our context due to the potential pre-determination of the variables. To achieve consistent estimates, a "within" estimation strategy requires strict exogeneity of the independent variables but this assumption could be too strong since market valuations may influence investment decisions concerning R&D, the patenting behaviour or the scientific disclosure strategies of firms. Although a sufficiently long time period can mitigate the problem of pre-determined variables, we additionally tested dynamic panel models by means of System-GMM estimators (Blundell and Bond, 1998) where we regard our knowledge stock measurements explicitly as pre-determined or endogenous and adapted the instrument lags correspondingly. Unfortunately, the model specification tests rejected the validity of the instrument sets, which prevented us from relying on these regression outputs.[15] Consequently, we focus on non-linear and linear estimations that use the cross-section variance and additionally on "within" and non-dynamic first-difference estimations. Acknowledging the limitations of the fixed-effect estimators in our context, we believe that they

[14] Hall and Oriani (2006) also tested the appropriateness of the approximation and found that it is not problematic if the R&D stock/Asset ratios do not exceed the value of 1, which applies to 85% of the firm-year observations in our sample. Above this margin, the non-linear estimation strategy can be regarded as somewhat superior.

[15] Nevertheless, we reported the regression results of a corresponding test in Table 7.

nevertheless have some informational value with respect to the question whether unobserved firm heterogeneity causes a severe bias or not.

4.4 Descriptive statistics

In Table 2, we provide an overview about the mean and median values as well as the standard deviation of the regression variables and some additional measures that are informative for describing the firm characteristics.

-- Insert Table 2 here --

Since all firms are stock-market listed, the sample consists predominantly of medium and large-sized firms. However, the median values suggest considerable heterogeneity among our sample firms. The median values are 7.39 million USD for the annual R&D expenditures, 73.94 million USD for sales and 334 for the number of employees whereas the mean values are much higher, indicating both the presence of very large but also medium sized and small firms. Overall, the R&D investments of the sample firms account for 66% of all business R&D expenditures in manufacturing sectors in the United States.[16] With respect to the firm's Tobin's Q, the average ratio is quite high with 2.56, whereas in 15.5% of the firm-year observations, the market valuation is below the book value.

Trends of publication outcomes within the sample period are shown in Table 3. The share of publishing firms increases from 40% in the year 1996 to 49% in the year 2003. This share is lower than the percentage of patenting firms, which reaches 61% in the year 2003.

-- Insert Table 3 here --

When considering both patenting and publishing simultaneously, it can be seen that both output types appear to be complementary since the majority of publishing firms in a given year also files a patent application. However, 10% of all firms publish but do not patent, 21% only patent, and 29% of the firms do neither patent nor publish in the year 2003. With respect to aggregated output numbers of the sample firms, the total number of patents increases considerably over time from 16,431 in 1996 to

[16] This percentage is based on the reference year 2003. The R&D in manufacturing sectors accounts for 139,064.87 Mio USD in year 2005 prices (see NSF 2007, page 16).

27,067 in 2003, while the total publication output slightly decreases between 1997 and 2001 before it reaches its peak in 2003. The strong increase in the patenting activity does not necessarily reflect increasing productivities but a stronger reliance on patents as a protection instrument. Although patent numbers exceed publication ones by the factor 2 in the year 2003, the publication amounts can nevertheless be regarded as impressive given that firms are by definition not concerned with contributions to the stock of scientific knowledge *per se*.

In Table 4, we display the bivariate correlations of the regression variables. Not taking multivariate interactions into account, we see a moderate positive correlation between all knowledge stock measures and the firm's Tobin's Q. The parallel inclusion of R&D, patent and publication stocks may raise concerns about multi-collinearity. Not surprisingly, we find notable but unproblematic correlations ranging from 0.26 to 0.34 between our core measures R&D/A, PAT/A, and PUB/A.

-- Insert Table 4 here --

Stronger concerns may arise from the variables that are additionally used in the extended model. The patent (publication)-based measures share those zeros that are originating from zero patent (publication) stocks, which implies some correlation by construction. Consequently, we detect relatively high correlations between publications with academic co-author and top-journal publications (0.63) or between science-based patents and broader patent scope (0.48). Despite these relatively high correlations between some explanatory variables we believe that, especially owing to the large size of our dataset, we can still provide valid statements on the impact of these additional measures.

5 Econometric results and discussion

5.1 Full sample estimations

The results of the econometric analysis are shown in Table 5. Following our considerations in the preceding Section, we estimated Tobin's Q both with non-linear and linear regression models. When comparing the non-linear with the equivalent linear models, it is apparent that signs and significant variables are consistent, which is in line with our argument that the linearization of equation (4) is a valid approximation and can consequently be used. In columns 1-5, we estimate the baseline specifications using NLLS, OLS, fixed effects and random effects estimators. Whereas the standard specification tests propose that random effects and OLS regressions are inconsistent, the results of all estimation procedures are very similar and the coefficients differ only marginally. With the exception of R&D stocks in the NLLS estimation, the three knowledge measures representing R&D (*R&D/A*), patent (*PAT/A*) and publication (*PUB/A*) stocks have a significant and positive effect on the Tobin Q indicator. This robust finding across all estimation procedures provides first indication that scientific publication stocks have a positive impact on the market value of firms above and beyond the influence of R&D and patent stocks.

-- Insert Table 5 here --

In order to obtain a more detailed picture, we introduced our additional measures that aim to capture the heterogeneity of scientific and inventive outcomes. In columns 6-10, we first added them independently to the baseline specifications using the NLLS estimator. It can be seen that all measures provide additional information and are all positive and significant. Here, not only the main patent stock variable remains robust to the inclusion of the additional measures but also the publication stock measure. More specifically, publication stocks (*PUB/A*) are significant at the 5% level when controlling for patent quality (*FWDCIT/PAT*), patent scope (*CLAIMS/PAT*) or science-based patents (*SCIPAT/PAT*). However, when including the additional publication measures that reflect the heterogeneity of scientific outcomes, the main effect gets weaker and turns insignificant in the models (9)-(10). This observation suggests that there is heterogeneity in the informational value of publications for financial markets and the firm's shareholders.

In columns 11-14, we display the regression results with the full variables set using NLLS, OLS, and fixed effect estimators. Starting with the models that do not take firm-fixed effects into account, it can be seen that R&D stocks (*R&D/A*), patent stocks (*PAT/A*) and patent quality (*FWDCIT/PAT*) are found to be significant, which is in line with the findings of previous studies (e.g. Hall et al. 2005). However, publication stocks (*PUB/A*) are not significant anymore in the model reported in column 11 but only the additional measure of publications in top-journals (*TOPPUB/PUB*). When testing the two measures for joint significance, the null-hypothesis of a zero-impact is rejected at the p-value 0.025. This suggests that there is still an impact of scientific contributions on the Tobin Q indicator while controlling for the nature of inventive outcomes and R&D. Interestingly, in the fixed effect models, the main effect (*PUB/A*) is positive and significant beyond the effect of R&D, patent stocks and patent quality, but publications in top-journals do not provide any premium. Hence, while overall the estimation models are consistent in suggesting a positive and significant effect of scientific publication stocks, the alternative estimation procedures propose some subtle differences depending on whether firm-fixed effects are taken into account or not. In other words, publication quality seems to matter for the determination of differences in the market valuation across firms whereas publication quality does not matter when controlling for unobserved firm-specific characteristics (like potentially relatively time-invariant research capabilities).

The question arises whether the effects found represent (i) an impact of basic research outcomes or the disclosure of it as an expression of firm openness, (ii) signalling benefits to academic audiences or the use of publications as an appropriation device like in the case of defensive publication. Unfortunately, we cannot provide conclusive evidence concerning these mechanisms with our measures but only offer some indications that have to be treated cautiously. In model 7, both scientific publication stocks as well as the stock of science-based patents are significant beyond the effects of R&D and patent stocks. Since the variable of science-based patents should at least partially capture the orientation of R&D with respect to its basicness, an additional effect of the scientific publication measure points to a positive impact of scientific disclosure per se. This interpretation finds some support by the full models where scientific publication stocks (together with publication in top-journals) remain significant. The non-significance of science-based patents in these models can be explained by the consideration that their effect is likely being absorbed by the patent forward citation measure. Although science-based patents are restricted to observed inventive outcomes, we believe it is a useful proxy for scientific research in firms given that our sample consists exclusively of firms from high-tech sectors with a high propensity to patent. As a robustness test, we modelled publication stocks orthogonally to patent stocks for a restricted sample of patenting firms, where the publication-patent ratio is positive and significant (see columns 3a and 3c in Table 7) beyond R&D, patent, and patent citation stocks. If one assumes a certain content overlap between published and patented knowledge, these results likewise suggest that disclosure itself provides valuable information to the financial markets beyond an engagement of companies in the creation of generic knowledge.

With respect to the second question, it can be emphasized that publication quality matters in the NLLS and OLS regression models. Since publishing in high-quality journals is not very attractive for the purpose of defensive publishing where firms have an interest in retaining control on the timing of disclosure (which is potentially more difficult with leading journals), these results suggest that the positive effect of top-journal publications may particularly reflect signalling benefits to upstream partners. However, beyond the defensive publication aspect, publication in high-quality journals may also be beneficial for adoption and marketing purposes. Since our fixed-effect estimations do not reveal an impact of journal quality, the results remain ambiguous. With our available measures, it is not possible to disentangle the effects more precisely and we have to leave deeper insights into this question to further research.

In column 1 of Table 6, we tested additionally for interaction-effects between publication and patent stocks (*PUB/A* x *PAT/A*), where the interaction effect is negative and significant while both main effects remain significantly positive with increasing magnitudes. In other words, the simultaneous presence of patent and publication stocks seems to weaken their respective informational value for the Tobin Q, which indirectly points to a certain content overlap between scientific and inventive knowledge.

Concerning our estimation strategy in general, the relatively consistent regression results across estimation techniques indirectly indicate that there is at least no huge bias originating from pre-determined variables and firm-specific time-invariant effects. In the following two subsections, we test whether the effects found are heterogeneous depending on sectors, firm size or estimation period and also display the results of further robustness tests.

5.2 Heterogeneity by sectors, firm size, periods

In order to detect potentially heterogeneous impacts of the scientific publication stocks on the Tobin Q indicator, we performed subsample regressions, distinguishing (i) the three most important meta-sectors, (ii) firm size and (iii) sub-periods. The relative differences between the subsample regressions are not found to be sensitive to the estimation procedure and therefore, we display and comment on the results of the NLLS estimations in Table 6.

-- Insert Table 6 here –

First, we ran separate regressions with the three meta-sectors biotechnology & pharmaceuticals, ICT's, and instruments. We detected some sector-specific patterns with respect to the influence of the knowledge stocks on the Tobin Q valuation. R&D stocks (*R&D/A*) are found to have a positive and significant impact in the pharmaceutical and instrument sectors but not in the ICT domain. However, patent stocks (*PAT/A*) are strongly significant and with a remarkable magnitude in ICT but have a lower impact in the other sectors, with patent stocks not being significant for pharmaceuticals. These results may indicate that R&D investments are a highly uncertain predictor for future commercial success in ICT's, whereas patent stocks clearly provide a valuable sign to the financial markets. Concerning the impact of scientific publication stocks *(PUB/A)*, we only see a positive and significant sign for scientific and medical instruments. It is interesting that publication stocks do not seem to be a predictor for market value in the pharmaceutical sector. This sector is traditionally regarded as strongly science-driven, with close interactions between firms and universities, and some firms being on the frontier of scientific knowledge production. The result could point to a limited informational value of scientific publications given the extensive publication activity in this sector and a relatively strong focus on basic research which is more uncertain with respect to future commercial returns.

Second, we distinguish between small and large firms based on the median workforce number (334 employees). In the subsample with the small firms (column 5), R&D and patent stocks are positive and significant at the 1% level while publication stocks are not significant. In the sample with the larger firms, R&D stocks are not significant and even have a negative sign, whereas both patent and publications stocks have a positive sign but only the publication variable is significant at the 1% level. Given the evidence provided by earlier work that firms with scientific capabilities achieve higher IPO placement amounts (Higgins et al., 2011), the result of a higher impact for larger firms is somewhat surprising. This finding could point to the possibility that the relative costs of science-related strategies are smaller for larger, more established firms which may have more resources and experience to handle disclosure as part of more comprehensive appropriation and signalling strategies.

Third, we split our sample in an early (1996-1999) and a late (2000-2003) period as reported in columns 7 and 8. Although the two sub-periods are relatively short, a difference in the valuation of knowledge assets would not be surprising given the "Dot-Com" boom in the late 1990s and the subsequent consolidation. Interestingly, our results show that the impact of R&D stocks decline, while we do not find notable differences with respect to the other measures. Overall, these robustness tests point to some heterogeneity concerning the impact of scientific publication stocks on the firm's market value.

5.3 Alternative specifications of the market value function and robustness tests

We performed several additional tests to discover the robustness of our results, which are reported in Table 7. These include the application of alternative variable specifications, knowledge depreciation rates, and econometric approaches.

-- Insert Table 7 here --

In the literature, patent stocks are frequently modelled as ratios over R&D rather than over assets (see Hall et al. 2005; Hall and Oriani 2006). As discussed in Section 3, we believe that it is more accurate to include all knowledge stocks as ratios over assets since these stocks do not necessarily reflect the same knowledge, for instance, due to time lags between the creation and codification of knowledge. In order to allow for comparisons with earlier studies, we estimated our regression models with these alternative specifications and also replicated the estimations by Hall et al. (2005) using R&D, patent, and patent citation stocks only. Starting with the latter (column 1a), we found that R&D and patent quality have a positive impact as documented in earlier work, but not the main patent stock variable. However, there is a straightforward technical explanation. Our filters trim observations above the highest 1% of the PUB/A & PAT/A ratios but do not capture exhaustively excessive PUB/R&D and PAT/R&D ratios. If the filters are adjusted correspondingly to trim the largest 1% of the

PUB/R&D and PAT/R&D ratios, we obtain regression results (column 1b) that are fully consistent with prior studies and also our regression outputs reported in Table 5. Adding the publication stock in column 2b, we obtain a positive and significant sign for *PUB/R&D* above and beyond the positive impacts of R&D, patent and patent citation stocks on Tobin's Q. Therefore, our findings are not sensitive to this alternative inclusion of the knowledge stock indicators.

A further possibility is to restrict the regression sample to patenting firms and to model publication stocks orthogonally to patent stocks. In the specifications 3a and 3c, the ratio of publication stocks over patent stocks (*PUB/PAT*) is positive and significant beyond the impacts of R&D, patent and patent quality stocks. As already mentioned in Section 5.1, if one assumes that publication and patent stocks reflect similar knowledge, this model would provide a rather strong indication that the disclosure component matters beyond a potential impact of basic research outcomes.

An assumption made in the literature is the accurateness of a depreciation rate of 15% for the knowledge stock variables. Since this standardized rate can only serve as an approximation that remains unproven, we varied the annual depreciation between 10% and 30%. These tested variations did not notably affect the regression results. However, R&D is only significant and positive when applying the high depreciation rates of 30% and 20% but not if a low depreciation rate of 10% is assumed. This finding is plausible from the viewpoint that, if knowledge gets obsolete faster, strong continuous investments into R&D should be of higher importance than in the case of a relatively persisting value deriving from previous R&D activities. Overall, the "true" knowledge depreciation rate is unknown and is unlikely to be constant across firms and time, but at least moderate variations do not seem to impact our findings.

To overcome the potential predetermination problems in our fixed-effect estimations, we tested the inclusion of pre-sample averages of the Tobin Q indicator as a control variable, as proposed by Blundell et al. (1995; 1999). This approach requires a notable pre-sample history of the Tobin Q measure to compute firm-specific pre-sample averages (Blundell et al., 1999). However, when imposing the (insufficient) requirement that a firm should be listed on the stock market for at least 4 years prior to the first sample year of 1996, we lose around 43% of all firm-year observations since many firms in our dataset had their IPO at a later point in time. As a consequence, we are not confident about the corresponding regression results. Moreover, to detect a potential bias of unobserved time-varying factors which are correlated with the error term and our explanatory variables, we tested dynamic panel specifications (see column 8). Unfortunately, we could not obtain valid estimates due to the lags of explanatory variables being invalid instruments (Sargan and Hansen test statistics are significant) despite testing different lag structures. Overall, as related studies, we could not address potential endogeneity sufficiently and acknowledge corresponding concerns.

6 Conclusion

This study examines the impact of scientific publication stocks of firms on their stock market valuation. Although scholars have started to address the determinants of scientific activities in firms, there is very little evidence on the payoffs and performance effects. We addressed this gap and provide novel empirical evidence using a rich dataset with firm-level information for US-American high-tech companies, combined with scientific publication and patent data. Our study contributes to the growing literature on boundary-spanning activities of firms and Open Innovation.

The findings of this study represent valuable evidence about an additional impact of scientific publication stocks on the firms' market valuation beyond the effects of R&D, patents and patent quality. Thanks to our comprehensive set of variables that captures the heterogeneity of scientific and inventive outcomes, we also found some indication that the positive effects of scientific knowledge stocks may not only represents benefits of achieving basic research outcomes but at least partially reflect benefits that are based on the *disclosure* of research outcomes itself. Although we could not precisely separate the underlying cause-effect mechanism (i.e. signalling to upstream partners vs. appropriation) and not fully rule out that some effects are endogenous, it has to be stressed that our regression results are quite robust concerning the positive impact of scientific publication stocks on Tobin's Q. Given that we controlled for several characteristics of the inventive outcomes, applied alternative estimation techniques and specifications of the market value function, and executed several robustness tests, our analysis provides a solid indication that scientific publication stocks in firms result in a more favourable stock market valuation.

This finding offers important insights to scholars and managers in firms, since it indicates that costly scientific research and the voluntary dissemination of research results to pursue signalling strategies can indeed be valuable. The results could encourage managers to consider corresponding openness approaches (e.g. to grant all scientists the right to publish), which would also be desirable from a social welfare point of view since many technologies and innovations are of a cumulative nature. However, our analysis also suggests that the impact of scientific activities is heterogeneous depending on the firm's context as some of our subsample regressions show.

Future work could focus on the contextual conditions that potentially moderate the relationship between scientific activities and firms' market value or consider additional industry sectors beyond the high-technology ones.

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Table 1: Scientific publications as indicator for financial markets

Publication as indication of…	Sign for market	Specific mechanism
Engagement in (basic) research	Positive	First-mover advantages Absorptive capacity Radical innovation
	Negative	Higher risk of failure than applied research & development Costly due to need for specialized equipment, Human Resource compositions and policies
Firm openness	Positive	Firm with access to academic information networks Firm with access to best graduates Valuable intermediate outcomes achieved Freedom to operate ensured and positive effects on adoption
	Negative	Knowledge spillovers Codification and opportunity costs

Table 2: Summary statistics

Variable	N	Mean	Std. Dev.	Median	Min	Max
TOBINS Q	7,022	2.56	2.29	1.79	0.26	19.54
A (BOOK VALUE)	7,022	1447.36	7130.88	82.91	0.55	273007.30
R&D EXP	7,022	93.24	415.93	7.39	0.00	12942.19
R&D STOCK	7,022	433.84	1800.52	34.86	0.00	30894.81
R&D/A	7,022	0.59	0.67	0.38	0.00	6.72
PAT/A	7,022	0.17	0.32	0.06	0.00	3.08
SCIPAT/PAT	5316	0.38	0.31	0.33	0.00	1.00
FWDCIT/PAT	5316	7.42	6.39	6.03	0.00	81.63
CLAIMS/PAT	5316	20.11	8.96	18.88	1.62	102.00
PUB/A	7,022	0.08	0.22	0.01	0.00	2.56
TOPPUB/PUB	4352	0.31	0.31	0.24	0.00	1.00
ACADPUB/PUB	4352	0.37	0.32	0.32	0.00	1.00
SALES	7,022	1164.84	5005.18	73.94	0.50	77613.83
EMPLOYEES	6,903	4002.89	14259.20	334.00	10.00	238000.00

financial amounts in Mio USD (2005, GDP deflated)

Table 3: Publication trends over time

	1996	1997	1998	1999	2000	2001	2002	2003
Perc. Patenting firms	50%	53%	55%	56%	57%	60%	60%	61%
Perc. Publishing firms	40%	41%	42%	43%	43%	43%	45%	49%
… only publishing	*10%*	*9%*	*10%*	*9%*	*9%*	*6%*	*8%*	*10%*
… patenting & publishing	*31%*	*32%*	*31%*	*34%*	*34%*	*37%*	*38%*	*40%*
… only patenting	19%	21%	23%	22%	23%	22%	22%	21%
… neither pat./publ.	41%	38%	35%	35%	35%	34%	32%	29%
Observations per year	*920*	*942*	*942*	*865*	*823*	*855*	*842*	*833*
Total Publications	12,504	12,697	12,393	10,983	10,629	10,278	11,370	13,283
Total Patents	16,431	20,515	20,384	19,786	23,335	26,043	27,466	27,067

Table 4: Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) LTOBIN'S Q	1.000												
(2) R&D/A	0.099	1.000											
(3) PAT/A	0.119	0.317	1.000										
(4) PUB/A	0.122	0.266	0.339	1.000									
(5) PAT/R&D	-0.012	-0.064	0.210	0.074	1.000								
(6) PUB/R&D	0.009	-0.058	0.089	0.336	0.427	1.000							
(7) FWDCIT/PAT	0.130	0.047	0.180	0.005	0.024	-0.022	1.000						
(8) SCIPAT/PAT	0.179	0.085	0.182	0.249	0.058	0.097	0.271	1.000					
(9) CLAIMS / PAT	0.118	0.008	0.242	0.098	0.065	0.038	0.469	0.479	1.000				
(10) TOPPUB/PUB	0.196	0.072	0.126	0.313	0.018	0.120	0.032	0.358	0.206	1.000			
(11) ACADPUB/PUB	0.153	0.069	0.129	0.235	0.023	0.109	0.115	0.331	0.258	0.632	1.000		
(12) SALES	0.053	-0.095	-0.063	-0.042	-0.015	-0.012	0.043	0.064	0.042	0.105	0.060	1.000	
(13) EMPLOYEES	0.022	-0.118	-0.072	-0.052	-0.016	-0.016	0.030	0.046	0.040	0.114	0.065	0.909	1.000

Table 5: Regression outputs

LOG TOBIN'S Q	(1) NLLS[1]	(2) OLS	(3) WITHIN	(4) FD	(5) RE	(6) NLLS	(7) NLLS	(8) NLLS	(9) NLLS	(10) NLLS	(11) NLLS[2]	(12) OLS	(13) WITHIN	(14) FD
	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)
R&D/A	0.026	0.048***	0.028*	0.065***	0.028**	0.040**	0.028	0.038**	0.026	0.028	0.039**	0.031**	0.029*	0.065***
	(0.018)	(0.016)	(0.015)	(0.019)	(0.011)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)	(0.015)	(0.015)	(0.019)
PAT/A	0.175***	0.155***	0.121***	0.125***	0.154***	0.118**	0.157***	0.133***	0.178***	0.173***	0.120**	0.093**	0.122***	0.125***
	(0.051)	(0.040)	(0.038)	(0.047)	(0.025)	(0.052)	(0.053)	(0.052)	(0.052)	(0.052)	(0.052)	(0.038)	(0.038)	(0.047)
PUB/A	0.132**	0.114**	0.149***	0.159**	0.113***	0.133**	0.105*	0.126*	0.052	0.084	0.058	0.045	0.144***	0.151**
	(0.063)	(0.050)	(0.047)	(0.067)	(0.033)	(0.064)	(0.063)	(0.065)	(0.061)	(0.062)	(0.062)	(0.046)	(0.048)	(0.067)
FWDCIT/PAT						0.012***					0.010***	0.007***	0.005***	0.003
						(0.002)					(0.002)	(0.002)	(0.002)	(0.002)
SCIPAT/PAT							0.136***				0.014	0.018	-0.015	0.011
							(0.039)				(0.042)	(0.036)	(0.033)	(0.040)
CLAIMS/PAT								0.004***			0.001	0.001	-0.002*	-0.001
								(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
TOPPUB/PUB									0.219***		0.167***	0.142***	0.055	0.066
									(0.047)		(0.055)	(0.044)	(0.039)	(0.044)
ACADPUB/PUB										0.159***	0.041	0.034	-0.041	-0.001
										(0.039)	(0.045)	(0.038)	(0.032)	(0.036)
SALES	0.009***	0.033***	0.063***	0.080***	0.025***	0.007***	0.008***	0.008***	0.758***	0.008***	0.006***	0.006***	0.062***	0.079***
	(0.002)	(0.006)	(0.013)	(0.017)	(0.005)	(0.002)	(0.002)	(0.002)	(0.040)	(0.002)	(0.002)	(0.002)	(0.013)	(0.017)
CONSTANT	0.768***	0.566***	0.892***	0.274***	0.647***	0.730***	0.753***	0.724***	0.007***	0.760***	0.720***	0.726***	0.889***	0.274***
	(0.049)	(0.046)	(0.060)	(0.013)	(0.208)	(0.047)	(0.041)	(0.045)	(0.002)	(0.039)	(0.037)	(0.038)	(0.061)	(0.013)
INDUSTRY CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
TIME CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-Year observations	7,022	7,022	7,022	5,394	7,022	7,022	7,022	7,022	7,022	7,022	7,022	7,022	7,022	5,394
Firm-IDs (cluster)	1,509	1,509	1,509	1,270	1,509	1,509	1,509	1,509	1,509	1,509	1,509	1,509	1,509	1,270
R^2	0.157	0.164	0.115	0.181	0.159	0.171	0.162	0.164	0.167	0.164	0.179	0.178	0.117	0.181

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[1] Semi-elasticities: R&D/A (0.014), PAT/A (0.025), PUB/A (0.009)

[2] Semi-el.: R&D/A (0.019), PAT/A (0.016), PUB/A (0.004), FWDCIT/PAT (0.045), SCIPAT/PAT (0.003), CLAIMS/PAT (0.007), TOPPUB/PUB (0.025), ACADPUB/PUB (0.008)

Table 6: Regressions with interaction effects and subsamples

LOG TOBIN'S Q	(1) Interact. NLLS Coeff (SE)	(2) Pharma NLLS Coeff (SE)	(3) ICT NLLS Coeff (SE)	(4) Instrum. NLLS Coeff (SE)	(5) Small firm NLLS Coeff (SE)	(6) Large firm NLLS Coeff (SE)	(7) Early Per. NLLS Coeff (SE)	(8) Late Per. NLLS Coeff (SE)
R&D/A	0.024	0.178***	-0.019	0.050	0.069***	-0.038	0.049**	0.016
	(0.018)	(0.058)	(0.021)	(0.032)	(0.022)	(0.042)	(0.025)	(0.019)
PAT/A	0.206***	-0.026	0.287***	0.144**	0.237***	0.044	0.210***	0.146**
	(0.056)	(0.146)	(0.087)	(0.069)	(0.064)	(0.084)	(0.054)	(0.063)
PUB/A	0.216***	0.052	-0.011	0.318**	0.097	0.394***	0.088	0.137
	(0.080)	(0.119)	(0.077)	(0.131)	(0.071)	(0.142)	(0.072)	(0.084)
PUB/A x PAT/A	-0.150**							
	(0.072)							
SALES	0.009***	0.013***	0.007*	0.012	1.212***	0.008***	0.010***	0.007***
	-0.002	(0.003)	(0.004)	(0.009)	(0.367)	(0.002)	(0.003)	(0.002)
CONSTANT	0.763***	0.709***	0.801***	1.167***	0.655***	0.759***	0.683***	0.732***
	(0.047)	(0.058)	(0.129)	(0.081)	(0.040)	(0.040)	(0.056)	(0.037)
INDUSTRY CONTR.	YES	YES	YES	YES	YES	YES	YES	YES
TIME CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
Firm-Year observations	7,022	1,387	3,095	2,411	3,511	3,511	3,669	3,353
Firm-IDs (cluster)	1,509	320	663	504	928	774	1,224	1,077
R^2	0.158	0.204	0.154	0.131	0.175	0.204	0.148	0.190

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Alternative specifications of the market value function and robustness tests

	(1a)	(1b)[1]	(2a)	(2b)[1]	(3a)	(3b)	(3c)[1]	(4)	(5)	(6)	(7)	(8)
	PUB & PAT stocks over R&D				PUB over PAT			D 30%	D 20%	D 10%	PRE-ST.	SYS-GMM[2]
LOG TOBIN'S Q	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	NLLS	FD
	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff (SE)	Coeff(SE)
R&D/A	0.069***	0.075***	0.069***	0.074***	0.030	0.072***	0.082***	0.075**	0.040*	0.014	0.027	0.015
	(0.018)	(0.018)	(0.018)	(0.018)	(0.024)	(0.022)	(0.023)	(0.032)	(0.022)	(0.013)	(0.030)	(0.033)
PAT/A					0.179***			0.353***	0.228***	0.129***	0.120	0.013
					(0.057)			(0.088)	(0.064)	(0.040)	(0.073)	(0.124)
PUB/A								0.167*	0.137*	0.115**	0.220**	0.418***
								(0.091)	(0.072)	(0.052)	(0.096)	(0.124)
PAT / R&D	-0.001	0.056**	-0.001	0.049**		-0.001	0.071***					
	(0.002)	(0.024)	(0.002)	(0.024)		(0.002)	(0.027)					
PUB / R&D			0.000	0.090**								
			(0.008)	(0.043)								
PUB / PAT					0.014***	0.011**	0.014**					
					(0.005)	(0.005)	(0.005)					
FWDCIT/PAT	0.014***	0.012***	0.014***	0.012***	0.013***	0.014***	0.013***					
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)					
PRE-SAMPLE Q / L.TOBINQ2											0.000***	0.086***
											(0.000)	(0.019)
SALES	0.007***	0.007***	0.007***	0.007***	0.008***	0.008***	0.008***	0.009***	0.009***	0.009***	-0.007**	0.085***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.027)
CONSTANT	0.728***	0.713***	0.728***	0.703***	0.690***	0.693***	0.667***	0.766***	0.767***	0.768***	21.576***	
	(0.050)	(0.049)	(0.050)	(0.047)	(0.048)	(0.051)	(0.050)	(0.048)	(0.049)	(0.048)	(5.907)	
INDUSTRY CONTR.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
TIME CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-Year observations	7,022	6,947	7,022	6,947	5,308	5,308	5,245	7,022	7,022	7,022	3,976	5,394
Firm-IDs (cluster)	1,509	1,503	1,509	1,503	1,174	1,174	1,167	1,509	1,509	1,509	714	1,270
R^2	0.165	0.166	0.165	0.168	0.185	0.178	0.181	0.163	0.158	0.155	0.214	-

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[1] Outlier filter (1%) applied to PUB/R&D and PAT/R&D ratios (instead of PUB/A and PAT/A)

[2] Lags: (3/5); Hansen and Sargan tests significant (instruments not reliable)

Appendix A.1: Key literature on the impact of knowledge assets on firm value

Study	*Knowledge stocks* R&D	PAT	PAT Q	Further distinctive elements (variables, scope, estimation strategy)	Sample size	Period
Griliches (1981)	Yes	Yes	No	"Within" estimation	1,091	1968-1974
Jaffe (1986)	Yes	Yes	No	Technological position, spillovers	432	1973-1979
Hall et al (1993)	Yes	No	No	Advertisting expenditures	24,333	1973-1991
Cockburn and Griliches (1998)	Yes	Yes	No	Appropriability and sector effects	722	1980
Blundell et al. (1999)	No	Yes	No	Innovation stock, industry-level variables, fixed effects	3,511	1972-1982
Deng et al. (1999)	Yes	Yes	Yes	Science-based patents	388 firms[1]	1985-1995
Bloom and Van Reenen (2002)	No	Yes	Yes	Market uncertainty	2,138	1968-1996
Lanjouw and Schankerman (2004)	Yes	Yes	Yes	Several patent quality measures; productivity and demand equation	11,464	1980-1993
Hall et al. (2005)	Yes	Yes	Yes	Patent citations	12,188	1963-1995
Hall and Oriani (2006)	Yes	Yes	No	European patents	2,156	1989-1998
McGahan and Silverman (2006)	Yes	Yes	Yes	Competitor spillovers	24,815	1981-1999
Hall et al. (2007)	Yes	Yes	Yes	European patents, quality index	5,312	1991-2002
Ceccagnoli (2009)	Yes	No	No	Appropropriability measures (incl. patent effectiveness)	330	1991-1993
Sandner and Block (2011)	Yes	Yes	Yes	Trademarks	6,757	1996-2002
Our study:	Yes	Yes	Yes	Scientific publications, heterogeneity of scientific & inventive outcomes and firms	7,022	1996-2003

[1] Observation number not reported

Appendix A.2: Comparing own matching outcome with NBER-benchmark

LOG TOBIN'S Q	(1) NLLS Coeff (SE)	(2) NLLS Coeff (SE)	(3) OLS Coeff (SE)	(4) OLS Coeff (SE)
R&D/A	0.026	0.026	0.048***	0.048***
	(0.018)	(0.018)	(0.016)	(0.016)
PAT/A	0.175***		0.155***	
	(0.051)		(0.040)	
PATNBER/A		0.173***		0.142***
		(0.056)		(0.044)
PUB/A	0.132**	0.149**	0.114**	0.131***
	(0.063)	(0.062)	(0.050)	(0.050)
SALES	0.009***	0.009***	0.033***	0.032***
	(0.002)	(0.002)	(0.006)	(0.006)
CONSTANT	0.768***	0.778***	0.566***	0.582***
	(0.049)	(0.054)	(0.046)	(0.049)
INDUSTRY CONTR.	YES	YES	YES	YES
TIME CONTROLS	YES	YES	YES	YES
Firm-Year observations	7,022	7,022	7,022	7,022
Firm-IDs (cluster)	1,509	1,509	1,509	1,509
R^2	0.157	0.156	0.164	0.162

Robust standard errors in parentheses;

*** p<0.01, ** p<0.05, * p<0.1

Appendix A.3: Data cleaning

Data cleaning and stepwise filters	N
Total observation number for regression analyis, period 1996-2003	10,139
Excluding firms with atypcial (negative) equity values	836
Excluding firms with ambiguous matches (patents, publications)	362
Filter for M&A (firm-year-obs. with annual book value change >300% or -75%	119
Excessive R&D/A, PAT/A, PUB/A, TOBIN's Q ratios (1%)	286
Small firms (<10 employees) and firms with Sales < 500.000 USD	558
Firms with R&D/Sales ratio > 1	956
Final regression sample	7,022 (69.3%)

Appendix A.4: Observations by included sectors

Meta-Sector	SIC included	Firm-year observations
Biotechnology & Pharmaceuticals	2834, 2835, 2836	1,112
Chemicals	2800, 2810, 2820, 2821, 2833	275
Telecommunication equipment & Semiconductors	3570, 3571, 3572, 3575, 3576, 3577, 3578, 3579, 3661, 3663, 3669, 3670, 3672, 3674, 3677, 3678, 3679, 4812, 4813, 4822	3,113
Aircraft & Aerospace	3721, 3724, 3728	111
Navigation, Scientific, Medical, Optical instruments	3812, 3822, 3823, 3824, 3825, 3826, 3827, 3829, 3841, 3842, 3843, 3844, 3845, 3851, 3861	2,411
Sum		7,022

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