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An empirical examination of the science–technology relationship in the biotechnology industry

Annapoornima M. Subramanian [a,*], Pek-Hooi Soh [b,1]

[a] Division of Engineering and Technology Management, National University of Singapore, Block E3A, #04-09 (Building E3A, Level 4, Room 9), 7 Engineering Drive 1, Singapore 117574, Singapore
[b] Segal Graduate School, Simon Fraser University, 500 Granville Street, Vancouver, BC, Canada V6C 1W6

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ABSTRACT

Understanding how a firm's scientific capability influences its technology development has important implications on the firm's research and development (R&D) strategies. However, the current literature reveals a puzzling outcome in its empirical investigations on the science–technology relationship. While many studies show the positive influence of a firm's scientific capability on its technological performance, a few others indicate that if a firm focuses its attention more on cutting edge science, its overall technological performance will suffer. We suggest that these findings can be reconciled by conceptualizing and measuring the scientific capability of the firm differently. This paper attempts to demonstrate how different notions of scientific capability are associated with different performance outcomes. Furthermore, a firm's scientific capability facilitates the integration of new knowledge to produce valuable technologies when a firm broadens its search for new knowledge. The paper highlights the nuances of conceptualizing and measuring the firm's scientific capability in two different ways: number of scientific publications and non-patent references. The findings also shed light on the mechanism through which science accelerates technological progress inside a firm.

* Corresponding author. Tel.: +65 65161645; fax: +65 6776 0755.
E-mail addresses: etmmsa@nus.edu.sg (A.M. Subramanian), psa28@sfu.ca (P.-H. Soh).
[1] Tel.: +1 778 782 7921; fax: +1 778 782 5153.

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1. Introduction

Scholars have long believed that scientific progress is a vital factor driving technological innovation and economic growth. At the macro level, studies have shown that total expenditures on research and development (R&D) and scientific employment drive a country's GDP (Mansfield, 1972; Sveikauskas, 1981; Adams, 1990). At the firm-level, scientific efforts and R&D efforts are known to improve firm capability and firm performance (Griliches, 1980; Henderson and Cockburn, 1994; Freeman and Soete, 2009). At the invention level, science-based patents originating from university labs are recognized to be more valuable (Jaffe and Trajtenberg, 1996; Gittelman and Kogut, 2003; Siegel et al., 2004). Therefore, understanding the relationship between science and technology has important implications for research and development activities. This study attempts to extend this stream of research by focusing on the science and technology relationship at the firm-level.

In explaining the relationship between science and technology, scholars have used the number of scientific publications produced by a firm to measure its scientific capability (Gambardella, 1992). While some studies have observed the positive influence of publication count on the technological performance of firms as measured by patent outcome (Lim, 2004), others have demonstrated that publication count is not associated with technological performance (Gambardella, 1995; Cockburn and Henderson, 1998). Yet, another study shows that when a firm generates cutting edge science, as represented by high quality publications, the technological performance of the firm will suffer (Gittelman and Kogut, 2003).

Recently, a growing number of studies exploring the science–technology relationship are using non-patent references in patents, i.e. citations of scientific publications, as an indicator of science intensity in a firm's capability or invention (Deng et al., 1999; Fleming and Sorenson, 2004; Sorenson and Fleming, 2004; Sorenson and Singh, 2006). These scholars found that non-patent references have a significant positive influence on technological performance in terms of patent outcome. However, a couple of studies have raised a concern regarding the appropriate use of non-patent references as the 'science-dependence' of the technology under study. Meyer (2000) has demonstrated that a citation to a scientific paper in a patent hardly represents any direct link between the cited paper and the patent. Noyons et al. (1994) have observed that inventors of patents with many non-patent references did not publish significantly more than inventors of patents with fewer non-patent References

The above mentioned studies highlight some inconsistent findings regarding the influence of scientific capability on technological performance. The discrepancy is partly a consequence of scholars using either of the two measures, namely publication volume and non-patent references, to evaluate scientific contributions to technological innovation without acknowledging their conceptual difference. Another contributing factor is that existing research has paid little attention to the mechanism through which scientific research influences technological performance (Fleming and Sorenson, 2004).

In order to improve our understanding of the science–technology relationship, we ought to recognize the conceptual difference between measuring scientific capability by publication count or by non-patent references, and explain their respective influences on technological performance. Drawing upon the absorptive capacity literature, this study suggests that publication count represents a firm's capability to generate scientific knowledge, whereas the count of non-patent references reflects a firm's capability to apply scientific knowledge towards developing new technologies. We test the relationship between each correlate and outcome using the publication and patent data of 157 biotechnology firms. The technological performance of firms is measured in terms of forward citations received by patents issued to the firms. The results show that the capability of firms to generate scientific knowledge has a significant negative influence on their technological performance. On the contrary, the capability of firms to apply scientific knowledge has a significant positive effect on their technological performance.

As a further attempt to reconcile the findings, this study investigates the means through which a firm's scientific outcome can accelerate its technological progress. Specifically, we investigate the contributions of the two scientific capabilities to the outcome of technological search breadth, i.e. when a firm broadens its search for new knowledge across multiple technology domains to generate useful technologies. The outcome of technological search breadth is proxied by observing the heterogeneity of technology classes cited by the patents granted to a firm. The empirical results indicate that a firm's publication count correlates positively with the outcome of technological search breadth, but the effect of non-patent references is not statistically significant. Taken together, the findings imply that although a firm's capability to apply scientific knowledge contributes directly to its technological performance, its capability to generate scientific publications becomes useful only when it attempts to integrate or combine diverse technological knowledge in the process of developing useful technologies.

This paper is organized as follows. Section 2 provides a theoretical framework and literature review. It focuses on the role of firm-level scientific capabilities in the science–technology relationship. Sections 3 and 4 describe the methods and research and measures. The last three sections discuss the research findings, implications, limitations of the study and directions for future research.

2. Theoretical framework and review of the literature

2.1. The relationship between science and technology

The notion of scientific research stimulating technological performance has been long established since Adam Smith (Stephan et al., 2007). Scientific research can enhance a firm's absorptive capacity (Cohen and Levinthal, 1990; Gambardella, 1992; Lim, 2000), serve as guideposts for technological investigation (Dasgupta and David, 1994; Autio et al., 1996; Aghion et al., 2009) and the management of research activities (Owen-Smith, 2001), etc. Thus, a firm's scientific research capability is expected to positively influence its technological performance and generate breakthrough technologies (Rosenberg, 1990). This is more so in the case of high-tech industries like biotechnology, the context chosen for this study (Zucker and Darby, 2001; Torero, 1998).

Lim (2000) has shown that science-driven firms tend to adopt two different strategies for building their scientific capabilities. First, firms invest in internal basic research that enables them to generate scientific findings. Second, firms develop capabilities to absorb scientific knowledge from external environments and apply this knowledge to the technology development process. Lim (2000) further suggests that firms need not acquire both types of capabilities, even though prior research points to the important role of internal basic research in absorbing external knowledge (Gambardella, 1995). He also posits that firms can develop their absorptive capacity through processes such as engaging in scientific collaborations, hiring individuals who have undergone rigorous scientific training, reading scientific papers published in the open scientific domain, etc. The constant engagement of highly trained scientists via these processes can help firms absorb external knowledge without necessarily conducting internal basic research. For instance, while firms like Merck invest heavily in internal scientific research and publish scientific articles, others like Eli Lily acquire absorptive capacity by leveraging externally generated scientific skills and knowledge.

Our literature review of the science–technology relationship reveals that most studies have implicitly captured the two types of scientific capabilities, namely the capability to generate scientific knowledge and the capability to apply scientific knowledge to technology development activities, using two different measures. Although the absorptive capacity literature makes a conceptual difference between the two scientific capabilities, the studies on the science–technology relationship do not explicitly stress the difference in measuring such scientific capabilities. The empirical studies have measured scientific knowledge generating capability by the number of scientific publications produced by firms and scientific knowledge application capability by the number of references to non-patent literature in patents issued to firms. The inconsistent findings surrounding the science–technology relationship are probably an outcome of using the two measures interchangeably without recognizing their conceptual difference. Following the recommendations of the absorptive capacity literature, this paper attempts to investigate the performance influence attributed to the different measures of scientific capabilities and reconcile the disparate findings by examining their respective roles in accelerating technological progress inside a firm.

2.2. Scientific capability, technological search breadth and technological performance

To understand how different scientific capabilities are instrumental in the process of generating useful technologies, we draw on insights from the literature of evolutionary search and investigate the importance of science to firms that engage in the search for new knowledge across diverse technological domains.

Organizations innovate by combining new knowledge with existing knowledge (Kogut and Zander, 1992). Thus, a firm's search for new technical knowledge is an inevitable part of its technological innovation process. Two types of search behavior are observed in innovative firms. The first is to look for new ideas in the neighborhood of research and development (R&D) activities within the firm. The second type of search requires the firm to span its organizational boundaries and look for external knowledge. In our study we refer to this boundary spanning search as 'new knowledge search'. Several studies have shown that new knowledge search is closely associated with a firm's capability to generate high-impact technologies (Rosenkopf and Nerkar, 2001; Ahuja and Lampert, 2001; Ahuja and Katila, 2004).

Prior research suggests that existing knowledge elements can be combined to create novel and valuable ideas (Tushman and Rosenkopf, 1992). In order to increase the amount of knowledge elements available for new combinations, a firm has to embark on a broad search for new knowledge. While different search strategies may hold different search criteria, in this study we define new knowledge search as a search of diverse technological domains, or 'technological search breadth' in short. When a firm attempts to move beyond existing technological landscapes and search broadly for different technological elements, it enriches the knowledge pool available to its in-house scientists and engineers. The enriched knowledge pool creates opportunities for cross-fertilization and cross-application of ideas, which may result in high-impact technologies. Particularly in the biotechnology industry, important innovations have evolved through new combinations of ideas found across multiple disciplines such as molecular biology, chemistry, bio-informatics, etc.

However, the process of combining diverse knowledge elements is not simple and straightforward. Identifying one fruitful combination among the many possibilities of technological recombination can be a daunting task. In this situation, scientific capability is known to provide a theoretical lens for firms to identify and evaluate useful combinations (Fleming and Sorenson, 2004).

How firms successfully recombine technological elements into valuable innovations may depend on the firms' understanding of the nature and interdependence of different technological knowledge elements or their own knowledge structures (Yayavaram and Ahuja, 2008). Scientific knowledge provides a basic understanding of the phenomena in question and the cause–effect relationships between technological elements, both of which are vital for recombination. Therefore, how firms develop their capabilities to generate scientific knowledge will shape their theoretical lens for discovering the novel ideas that may lead to useful technologies. An excellent example of this in our research context is the birth of genetic engineering. It is well known that the scientific capabilities of Dr. Stanley Cohen[2] and Dr. Herbert Boyer[3] had helped them realize the value of combining the technique of introducing new DNA into *Escherichia coli* with the technique of cleaving the double-stranded DNA molecule, which is the building block of genetic engineering.

Following the arguments presented above, the next section proposes to test the relative performance impacts of two scientific capabilities, namely the capability to generate scientific knowledge (as represented by a firm's publication count) and the capability to apply scientific knowledge to technological innovation (as represented by non-patent references in patents issued to a firm). The count of forward citations of patents issued to the firm is used as a proxy for the firm's technological performance. The next section also analyzes the respective contributions of the two scientific capabilities to the outcome of technological search breadth. A firm's technological search breadth is measured by the heterogeneity of the technology class of backward citations made in patents issued to the firm.

3. Data

The biotechnology industry is an ideal context for this study because it is characterized by intense innovation and widely recognized for valuing scientific research. The Plunkett's[4] Directory that

[2] A professor from the Stanford University.

[3] A professor from the University of San Francisco.

[4] Plunkett's *Biotech and Genetics Industry Almanac 2005:* the only comprehensive guide to biotechnology and genetic companies and trends/editor and publisher: Jack W. Plunkett.

Table 1
U.S. patent classes.

Class	Description
424	Drug, bio-affecting and body treating compositions
435	Chemistry: molecular biology and microbiology
436	Chemistry: analytical and immunological testing
514	Drug, bio-affecting and body treating compositions
530	Chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products thereof
536	Organic compounds
800	Multicellular living organisms and unmodified parts thereof and related processes

consists of 437 publicly-listed biotechnology firms was used as the primary data source for drawing the sample. Prior studies have typically relied on various biotechnology directories for data collection (Gulati and Singh, 1998; Stuart et al., 1999). The 437 publicly-listed companies are considered to be leaders in all facets of the biotechnology industry. Though the directory is known for its carefully researched volumes with frequent updates, it should be acknowledged that the directory concentrates only on leading firms (measured in terms of sales volume) unlike other directories that have a comprehensive list of companies from this industry. Nevertheless, our sample is comparable to the samples from other biotechnology-related studies that have appeared in internationally refereed research journals.

Most firms in this directory are based in the U.S. However, about 70 have their headquarters in other countries such as Canada, Japan, UK, India, Switzerland, etc. The directory also includes firms from multiple areas of biotechnology. There are 3 firms from agriculture, 13 firms from infotech, 100 firms from chemical manufacturing, and 321 firms from health care.

The sample firms' patents by issue date from 1990 to 2000 were obtained from the NUS-MBS patent database[5] which contains all patent data managed by the United States Patent and Trademark Office (USPTO). The publication data of the sample firms were gathered from the *Web of Science*, *ISI Science Citation Index* (*SCI*). The SCI is an excellent source for covering a broad range of basic and applied scientific journals (Lim, 2004). Finally, Compustat Global was used to collect the financial data of these firms.

The US patent classification system comprises of over 100,000 patent subclasses aggregated to about 400 three-digit patent classes. We used the three-digit patent classes as listed in Table 1 to identify all the patents that belong to the biotechnology industry. These classes were chosen with reference from the USPTO Technology Profile Reports and from prior research (Lim, 2004). Excluding firms that did not have patents in the specified classes between 1990 and 2000, the final sample was reduced to 222 firms. The total numbers of patents and publications used in the final analysis are 10,646 and 100,375, respectively.

4. Measures

4.1. Technological performance (forward citation)

The dependent variable is cumulative forward citation frequency accrued to each patent. We count all forward citations received by each patent at of the end of 2004. Every patent, by law, must cite previous patents that relate closely to its own technology. Past research demonstrates that the number of forward citations a patent receives correlates highly with its technological importance (Trajtenberg, 1990; Albert et al., 1991). Forward citation is also used in representing the extent to which the patent is widely diffused because of its technological importance.

The number of products introduced by a firm would be a good alternative measure of technological performance. However, we do not use this product measure for two reasons. First, currently, the upstream activities of the value chain in this industry are typically performed by firms competent in those areas, whereas other firms take care of FDA approval and commercialization. Hence, a firm that introduces a new product into the market may not necessarily be the one fully responsible for its technological development. Second, the approval of a new drug product, which is often time

[5] http://mbs.edu/patents/.

consuming, depends significantly on the focal firm's experience in dealing with external institutions, such as hospitals for clinical trials and the U.S. Food and Drug Administration (FDA), rather than on technological competency alone. Therefore, a drug that fails to gain FDA approval may not imply a lack of technological performance in the focal firm. Similarly, not all useful patents will lead to immediate drug development within the focal firm. For these reasons, we believe that patent count is a more appropriate measure of a firm's capability to generate valuable technologies.

4.2. Publication volume

This variable measures the number of scientific publications produced by the focal firm during the year of observation in which a patent was filed. The volume of scientific publications indicates the capability of the firm to generate scientific knowledge (Gittelman and Kogut, 2003). For all publications in *Web of Science* there is a field called "Organization Name" that typically lists the organizations the authors are affiliated to. To obtain the publication volume measure, we searched *Web of Science* for all scientific publications that had our sample firms listed under the "Organization Name" field.

4.3. Non-patent reference

Non-patent reference is the frequency count of references to non-patent literature, e.g. scientific literature, in each patent issued to a firm. Every patent is required to list the prior art that it builds upon. This includes both patent and non-patent references. It has been observed by Fleming and Sorenson (2004) that about 69% of non-patent references are from peer-reviewed scientific journals. The non-patent references that denote the science intensity of patents represent a firm's ability to apply scientific knowledge to its technological activities (Ahuja and Katila, 2004). In this study, the average number of non-patent references cited by a patent is 18.

4.4. Breadth of new knowledge search (technological search breadth)

Breadth of new knowledge search refers to the breadth of technological search conducted by the focal firm. This measure is based on the technology class of patents cited by each patent issued to the firm (after removing self-citations). Specifically, technological search breadth as represented in patent i is calculated as

$$1 - \sum_{j=1}^{n_i} S_{ij}^2 \ \text{(one minus the Herfindahl concentration index of the technology classes)}$$

where S_{ij} refers to the proportion of citations made by patent i to the patents in technology class j (after removing self-citations). The variable n_i varies for each patent depending on the number of different technology classes that the focal patent cites. The three-digit technology class is considered in the measure. This measure ranges between 0 and 1; a greater value implies a higher degree of technological search breadth is associated with the patented technology. This measure corresponds to the "originality" measure in the work of Jaffe and Trajtenberg (2002).

4.5. Control variables

Seven control variables related to firm-level and patent-level attributes are included in the regression analysis. The total count of forward citations received by the focal firm may be explained by various factors such as firm size, firm age and technological strength. Controlling for these variables should help reveal the performance effects of scientific capabilities.

4.6. Firm-level attributes

4.6.1. Firm size, firm age, R&D expenditure and technological strength

Firms may be highly innovative for different reasons. Larger firms can achieve high performance because of their economies of scale and scope, whereas younger firms may possess creative ideas

Table 2
Descriptive statistics and correlations.

No.	Variables	Mean	Std. dev	Min	Max	1	2	3	4	5	6	7	8
1	Forward citation	6.34	11.87	0	233	1							
2	Publication volume	136.39	222.74	0	1272	−0.06*	1						
3	Non-patent reference	18.36	35.14	0	492	0.05*	−0.01	1					
4	Breadth of new knowledge search	0.35	0.29	0	0.98	0.11*	−0.06*	0.16*	1				
5	Firm age	3.37	1.21	0	5.01	−0.18*	0.14*	−0.23*	−0.01*	1			
6	Firm size	6.82	2.32	0	11.69	−0.10*	0.00	−0.06*	−0.03*	0.53*	1		
7	R&D	3.04	2.15	−0.55	12	0.17*	−0.30*	0.05*	0.06*	−0.57*	−0.69*	1	
8	Technological strength	62.86	61.33	1	240	−0.16*	0.18*	0.02	0.00	0.46*	0.62*	−0.65*	1
9	Patent age	10.12	2.80	7	17	0.28*	0.11*	−0.15*	0.03*	0.07*	0.01	0.06*	−0.09*

* $p<0.05$.

because of their organic structures and talented founders (Nystrom et al., 2002). To control for these effects, we included the size of the firm as measured by the number of employees and the age of the firm as measured by the number of years since the firm was founded. A firm's performance can also be influenced by its technological resources and strength. We controlled for a firm's technological resources by considering the firm's R&D expenditure and its technological strength as measured by the total number of patents granted to the firm in the year of observation (Cardinal and Hatfield, 2000). We included the logarithmic values of firm size, firm age and R&D expenditure in our analysis.

4.7. Patent-level attributes

4.7.1. Technology class, patent age and year-fixed effect

Patents belonging to a certain technology class may inherently be more frequently cited than others. Similarly, patents that have elapsed for many years since their filing dates are likely to be cited more often. We used technology class dummy variables and patent age to control for these effects. We also used year-fixed effects to capture the differences in citation probability across different years.

The summary data for the dependent and independent variables and the correlation between the variables are reported in Table 2.

5. Analysis

The dependent variable is forward citation count, thus count models are most appropriate for this research. The Poisson model and the negative binomial model are frequently used for analyzing count data. As the patent citations exhibit overdispersion, the negative binomial model is best suited for estimating an overdispersed parameter. The results of the negative binomial regression are presented in Table 3. All specifications include fixed effects for both technology class and application year of the patents. We used robust standard errors adjusted for clustering of the firms to control for random firm effects. Though our sample has 222 firms and 10,606 patents, due to missing observations, the final regression results are based on 157 firms and 7648 patents.

Model 1 presents the regression coefficients for all of the control variables. As expected, firm age has a negative impact on the forward citation of patents ($p<0.01$). Firm size and R&D expenditure do not have significant associations with the forward citation of patents. A plausible explanation for the insignificant role of R&D and firm size is that increased R&D spending and economies of scale need not necessarily increase the quality of technologies, as measured by the forward citations. The technological strength of a firm, as measured by the number of patents it generates, is negatively associated with the forward citation of patents ($p<0.01$). This shows that the quality of patents is inversely proportional to the quantity generated. The significant ($p<0.01$) positive effect of patent age shows that older patents receive more citations.

Model 2 includes the first scientific capability variable, publication volume. In contrast to our prediction, the publication volume variable is negatively associated with the forward citation of

Table 3
Negative binomial regression in testing the impact of scientific capability, breadth of new knowledge search and control variables on the forward citation of patents.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	0.2256	0.2256	−0.2060	−0.2205	−0.1576	−0.0680	−0.3817	−.02292
	[0.3803]	[0.3803]	[0.4133]	[0.3434]	[0.3581]	[0.3177]	[0.3750]	[0.3441]
Publication volume		−0.0004***			−0.0004***	0.0000		−0.0000
		[0.0001]			[0.0001]	[0.0001]		[0.0001]
Non-patent references			0.0033***		0.0026***		0.0042**	0.0046***
			[0.0012]		[0.0012]		[0.0021]	[0.0020]
Breadth of new knowledge search				0.6320***	0.5741***	0.7782***	0.6375***	0.7930***
				[0.1621]	[0.1703]	[0.1875]	[0.1654]	[0.1816]
Publication volume × breadth of new knowledge search						0.0011***		0.0012***
						[0.0004]		[0.0004]
Non-patent references × breadth of new knowledge search							0.0029	0.0034
							[0.0028]	[0.0026]
Firm age	−0.2483	−0.2483***	−0.2271***	−0.2394***	−0.2208***	−0.2379***	−0.2199***	−0.2171***
	[0.0576]	[0.0576]	[0.0616]	[0.0532]	[0.0546]	[0.0506]	[0.0569]	[0.0541]
Firm size	0.0416	0.0416	0.0645**	0.0479*	0.0296	0.0270	0.0482*	0.0261
	[0.0350]	[0.0350]	[0.0355]	[0.0335]	[0.0325]	[0.0322]	[0.0333]	[0.0321]
R&D	0.0209	0.0209	0.0450*	0.0282	0.0073	0.0063	0.0293	0.0065
	[0.0316]	[0.0316]	[0.0275]	[0.0287]	[0.0291]	[0.0304]	[0.0275]	[0.0289]
Technological strength	−0.0022	−0.0022***	−0.0027***	−0.0023***	−0.0022***	−0.0019***	−0.0024***	−0.0021***
	[0.0006]	[0.0006]	[0.0006]	[0.0006]	[0.0005]	[0.0006]	[0.0006]	[0.0005]
Patent age	0.1732	0.1732***	0.1766***	0.1744***	0.1797***	0.1755***	0.1779***	0.1792***
	[0.0218]	[0.0218]	[0.0216]	[0.0213]	[0.0218]	[0.0215]	[0.0214]	[0.0217]
Log likelihood	−20554.75	−20554.75	−20541.31	−20495.47	−20466.44	−20469.78	−20478.20	−20450.34
No. of observations	7648	7648	7648	7648	7648	7648	7648	7648

Standard error is provided in the parentheses. Technology class dummy variables and year-fixed effect were included but not reported.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

patents ($p < 0.01$). A plausible explanation for this anomaly is presented in Section 7. On the contrary, the second scientific capability measure, the non-patent references introduced in Model 3, is positively associated with the forward citation of patents.

Model 4 presents regression coefficients when technological search breadth is included. As predicted, the broader the technological search the greater the technological performance. Model 5 presents the results when all three variables are considered together. The results are consistent with previous models.

Model 6 presents the results when the interaction term between publication volume and technological search breadth is introduced. Similarly, Model 7 adds the interaction term between non-patent references and technological search breadth. Model 8 presents the regression results when both interaction terms are added. The results show that the interaction term for technological search breadth and publication volume is positively significant ($p < 0.01$), but that the interaction term for technological search breadth and non-patent references is not statistically significant (after controlling for the number of publications in Model 8). The next section presents a detailed discussion of the results.

6. Discussion, implications, and directions for future research

The notion of scientific capability has been widely adopted in many empirical studies of the science–technology relationship, but its association with the technological performance of the firm, as measured by the forward citation of firm patents, receives mixed findings. While scientific capability is typically measured by (1) publication volume and (2) non-patent references, prior studies use these measures interchangeably to indicate the degree or importance of science contributing to a firm's technological development. This study aims to empirically distinguish the two measures and highlight that they have different implications for technological performance. Using panel data from 157 firms and 7648 patents in the biotechnology industry, the longitudinal analysis shows that non-patent references have a direct positive effect on a firm's technological performance, whereas publication volume has a negative impact on technological performance.

To further understand the two measures of scientific capability we investigated the association between them. We observed publication volume to be negatively correlated with the non-patent references in our data, indicating the possibility that firms with a high publication volume failed to apply their scientific knowledge to develop patented inventions. We suspect that the lack of an ability to apply scientific knowledge can be attributed to a knowledge gap between the science and the technology domains within firms. The knowledge gap prevents these firms from exploiting scientific knowledge in their technology development endeavors (Gittelman and Kogut, 2003). The gap between basic and applied knowledge can possibly explain the mixed findings regarding the science–technology relationship.

To verify our conjecture, we examined the extent to which the publications of individual sample firms are being self-cited in their patents. We first identified all publications produced by the focal firm and all patents citing those publications. We then checked the first assignee name of the citing patents to see whether the patents belong to the focal firm. We found that approximately 2% of the sample firms' scientific publications are cited by their own patents. Notably, this result is consistent with Noyons et al.'s (1994) observation about patent inventors. He observed that inventors with a greater number of publications are not necessarily associated with a greater number of non-patent references in their patents. It is the flow of knowledge across scientific publications and patented inventions that determines the influence of a firm's scientific capability on its own technological performance (Azoulay et al., 2007).

The above findings have important empirical implications. Firstly, the results suggest that the influence of scientific capability on a firm's technological performance may vary depending on the way that scientific capability is measured. Scholars need to be wary of conceptualization and measurement of scientific capability when interpreting their results about the science–technology relationship. Secondly, scholars investigating the science–technology relationship should give due attention to the knowledge gap that exists between the science and technology domains and also investigate mechanisms that could possibly bridge them (Gittelman and Kogut, 2003).

We further examined the difference between the two scientific capability measures in contributing to a firm's ability to recombine diverse technological elements. The results suggest that the publication volume measure enhances a firm's recombination capability, but the non-patent reference measure does not. This suggests that the tacit knowledge attained through the process of publishing papers provides firms with a useful lens to comprehend the attributes of new technological elements and their interdependency and to predict the fruitful combinations that lead to valuable innovations. Existing studies suggest that scientific capability facilitates technological recombination (Ahuja and Katila, 2004).

However, Henderson and Cockburn (1994) argue that the integration of diverse knowledge in the form of valuable innovations depends on a firm's core competence, which is not measurable by mere R&D investments. While a firm's scientific capability can be captured in different ways, the process through which a firm searches for new knowledge across multiple technological areas, such as knowledge boundary spanning activities, can only be assisted by the firm's experience in basic research or research publications.

This research is subject to the following limitations. The first limitation pertains to patent data and holds for any study on the science–technology relationship that uses patents. Restricting the scope of this study to patent data has several drawbacks because not all companies have the same propensity to file patents for their inventions; some firms may limit their patents to only the most successful innovations, etc. Nevertheless, it is widely recognized that in high-tech industries firms actively engage in a patent race and that patents are considered a good indicator of technological performance (Levitas et al., 2006; Gittelman and Kogut, 2003; Sorenson and Fleming, 2004; Ernst, 1998). Future studies can investigate differences in the influence of the two scientific capability measures on other firm-level performance variables like the number of new products generated and revenue from commercializing and licensing patents (Lai and Che, 2009).

The second limitation points to the forward and backward citations of patents, which we used for measuring our dependent and independent variables. It is noted that about 40% of the citations in patents are added by patent examiners for legal reasons (Alacer and Gittelman, 2006). However, this limitation is mitigated by the way that citations are used in the study. Forward citations, whether made by firms or included by examiners, can be said to represent the value of the patent. The breadth of new knowledge search measure, even if some of the citations were included by examiners, signifies that the focal firm has implicitly made use of the knowledge. As patents issued after 2000 explicitly list citations included by examiners, future studies can investigate this phenomenon after excluding the examiner's citations.

The third limitation is pertaining to publications. Not all firms involved in scientific research have the inclination to disclose their findings through publishing. Even among publications, articles can be classified as basic and applied (Lim, 2004). A fine grained approach to categorizing publications, citations and co-citations could be a possible avenue for future research and such a study could provide important insights into the science–technology relationship (Deeds, 2001; Frenken et al., 2005).

Fourth, a count of all non-patent references was taken into consideration when measuring scientific capability. A more appropriate measure would have been to consider citations to scientific publications. However, this limitation is to some extent mitigated by the observation by Fleming and Sorenson (2004) that the majority of non-patent references are in fact citations to scientific publications. Some scholars even question the appropriateness of using non-patent references to measure the science intensity of patents (Onder and Bart, 2008).

7. Conclusion

Understanding the science–technology relationship is of strategic importance for making R&D decisions. While several studies have explored this relationship, our study extends this line of research by highlighting the difference between the two measures of scientific capability that have been widely used by scholars, and demonstrates their varied effect on a firm's technological performance. Our findings suggest that scholars must be wary of interpreting results pertaining to the science–technology relationship, depending on the operationalization of the variables. By delineating the difference between the two measures of scientific capability, our research makes an important empirical contribution by explaining the mixed findings regarding the science–technology relationship in previous studies.

References

Adams, J.D., 1990. Fundamental stocks of knowledge and productivity growth. Journal of Political Economy 98, 673–702.
Aghion, P., David, P.A., Foray, D., 2009. Science, technology and innovation for economic growth: linking policy research and practice in STIG systems. Research Policy 38, 681–693.
Ahuja, G., Katila, R., 2004. Where do resources come from? The role of Idiosyncratic situations. Strategic Management Journal 25, 887–907.
Ahuja, G., Lampert, C.M., 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal 22, 521–543.
Alacer, J., Gittelman, M., 2006. Patent citations as a measure of knowledge flows: the influence of examiner citations. The Review of Economics and Statistics 88, 774–779.
Albert, M., Avery, D., Narin, F., McAllister, P., 1991. Direct validation of citation counts as indicators of industrial important patents. Research Policy 20, 251–259.
Azoulay, P., Ding, W., Stuart, T., 2007. The determinants of faculty patenting behavior: demographics or opportunity. Journal of Economic Behavior and Organization 63, 599–623.
Autio, E., Hameri, A., Nordberg, M., 1996. A framework of motivations for industry-big science collaboration: a case study. Journal of Engineering and Technology Management 13, 301–314.
Cardinal, L.B., Hatfield, D.E., 2000. Internal knowledge generation: the research laboratory and innovative productivity in the pharmaceutical industry. Journal of Engineering and Technology Management 17, 247–271.
Cockburn, I., Henderson, R.M., 1998. Absorptive capacity, co-authoring behavior and the organization of research in drug discovery. Journal of Industrial Economics 46, 157–182.
Cohen, W.M., Levinthal, D., 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35, 128–152.
Dasgupta, P., David, P., 1994. Towards a new economics of science. Research Policy 23, 487–521.
Deeds, D.L., 2001. The role of R&D intensity, technical development and absorptive capacity in creating entrepreneurial wealth in high technology start-ups. Journal of Engineering and Technology Management 18, 29–47.
Deng, Z., Lev, B., Narin, F., 1999. Science and technology as predictor of stock performance. Financial Analysts Journal 53, 20–32.
Ernst, H., 1998. Patent portfolios for strategic R&D planning. Journal of Engineering and Technology Management 15, 279–308.
Fleming, L., Sorenson, O., 2004. Science as a map in technological search. Strategic Management Journal 25, 909–928.
Freeman, C., Soete, L., 2009. Developing science, technology and innovation indicators: what we can learn from the past. Research Policy 38, 583–589.
Frenken, K., Holzl, W., de Vor, F., 2005. The citation impact of research collaborations: the case of European biotechnology and applied microbiology. Journal of Engineering and Technology Management 22, 9–30.
Gambardella, A., 1995. Science and Innovation: The U.S. Pharmaceutical Industry During the 1980s. Cambridge University Press, Cambridge.
Gambardella, A., 1992. Competitive advantage from in-house scientific research: the US pharmaceutical industry in the 1980s. Research Policy 21, 391–407.
Gittelman, M., Kogut, B., 2003. Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. Management Science 49, 366–382.
Griliches, Z., 1980. Returns to research and development expenditures in the private sector. In: Kendrik, J., Vaccara, B. (Eds.), New Developments in Productivity Measurement and Analysis. University of Chicago Press, Chicago, pp. 419–454.
Gulati, R., Singh, H., 1998. The architecture of cooperation: managing coordination uncertainty and interdependence in strategic alliances. Administrative Science Quarterly 43, 781–814.
Henderson, R., Cockburn, I., 1994. Measuring competence? Exploring firm effects in drug discovery. Strategic Management Journal 15, 63–84.
Jaffe, A.B., Trajtenberg, M., 2002. Patents, Citations & Innovations: A Window on the Knowledge Economy. MIT Press, Cambridge.
Jaffe, A.B., Trajtenberg, M., 1996. Flows of knowledge from universities and federal labs: modeling the flow of patent citations over time and across institutional and geographic boundaries. Proceedings of the National Academy of Sciences of the United States of America 93, 12671–12677.
Kogut, B., Zander, U., 1992. Knowledge of the firm, combinative capabilities and the replication of technology. Organization Science 3, 383–397.
Lai, Y.H., Che, H.C., 2009. Evaluating patents using damage awards of infringement lawsuits: a case study. Journal of Engineering and Technology Management 26, 167–180.
Levitas, E.F., McFadyen, M.A., Loree, D., 2006. Survival and the introduction of new technology: a patent analysis in the integrated circuit industry. Journal of Engineering and Technology Management 23, 182–201.
Lim, K., 2004. The relationship between research and innovation in the semiconductor and pharmaceutical industries 1981–1997. Research Policy 33, 287–321.
Lim, K., 2000. Basic research, applied research and innovation in the semiconductor and pharmaceutical industries. Unpublished dissertation at the Massachusetts Institute of Technology.
Mansfield, E., 1972. Contribution of R&D to economic growth in the United States. Science 175, 477–486.
Meyer, M., 2000. Does science push technology? Patents citing scientific literature. Research Policy 29, 409–434.
Noyons, E.C.M., van Raan, A.F.J., Grupp, H., Schmoch, U., 1994. Exploring the science and technology interface: inventor–author relations in laser medicine research. Research Policy 23, 443–457.
Nystrom, P.C., Ramamurthy, K., Wilson, A.L., 2002. Organizational context, climate and innovativeness: adoption of imaging technology. Journal of Engineering and Technology Management 19, 221–247.

Onder, N., Bart, V., 2008. Knowledge flows, patent citations and the impact of science on technology. Economic Systems Research 20, 339–366.
Owen-Smith, J., 2001. Managing laboratory work through skepticism: processes of evaluation and control. American Sociological Review 66, 427–452.
Rosenkopf, L., Nerkar, A., 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disc industry. Strategic Management Journal 22, 287–306.
Rosenberg, N., 1990. Why do firms do basic research with their own money? Research Policy 19, 165–174.
Siegel, D.S., Waldman, D.A., Atwater, L.E., Link, A.N., 2004. Toward a model of the effective transfer of scientific knowledge from academicians to practitioners: qualitative evidence from the commercialization of university technologies. Journal of Engineering and Technology Management 21, 115–142.
Sorenson, O., Fleming, L., 2004. Science and the diffusion of knowledge. Research Policy 33, 1615–1634.
Sorenson, O., Singh, J., 2006. Science, social networks and spillovers. INSEAD Working Paper, Reference: 2006/09/ST.
Stuart, T.E., Hoang, H., Hybels, R., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Administrative Science Quarterly 44, 315–349.
Stephan, P.E., Gurmu, S., Sumell, A.J., Black, G., 2007. Who's patenting in the university? Evidence from the survey of doctorate recipients. Economics of Innovation and New Technology 16, 71–99.
Sveikauskas, L., 1981. Technological inputs and multifactor productivity growth. Review of Economics and Statistics 63, 275–282.
Torero, M., 1998. Analyzing the spillover mechanism on the semiconductor industry in the Silicon Valley and Route 128. Essays on Diffusion of Technical Change. Unpublished Ph.D. dissertation. UCLA Economics Department, Los Angeles, CA.
Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. RAND Journal of Economics 21, 172–187.
Tushman, M.L., Rosenkopf, L., 1992. Organizational determinants of technological change: toward a sociology of technological evolution. Research in Organizational Behavior 14, 311–347.
Yayavaram, S., Ahuja, G., 2008. Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. Administrative Science Quarterly 54, 333–362.
Zucker, L.G., Darby, M.R., 2001. Capturing technological opportunity via Japan's star scientists: evidence from Japanese firms' biotech patents and products. Journal of Technology Transfer 26, 37–58.