Technological knowledge breadth and depth: performance impacts

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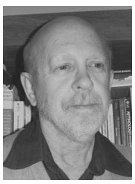

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Abstract

Purpose – *The purpose of this paper is to explore how the depth and breadth of firms' technological knowledge affect their performance.*

Design/methodology/approach – *An empirical investigation of a sample of US manufacturing firms was conducted. The main independent variables were measured using firms' patent data. Three hypotheses based on theory were developed and tested using multivariate regressions. To increase reliability, alternative industry and firm explanators of performance are controlled.*

Findings – *The depth and breadth of technological knowledge, rather than total stock, are significantly better at predicting three measures of firm performance that was used in the study – return on invested capital, sales growth, and Tobin's* q. *The two knowledge dimensions exhibited either independent non-linear effects or mutually reinforcing effects on each of the three performance measures.*

Research limitations/implications – *The study is limited to a fine-grained analysis of effects of technological knowledge. It does not take into account the facilitating role of marketing and administrative knowledge.*

Practical implications – *Corporate managers need to measure the depth and breadth of their technological knowledge stocks and include them in their planning models. Extreme combinations of depth and breadth need to be corrected and brought into balance.*

Originality/value – *The paper represents one of the few studies to disaggregate a firm's total stock of technological knowledge into its depth and breadth components.*

Keywords *Performance management, United States of America*

Paper type *Research paper*

1. Introduction

Few would argue against the proposition that technological knowledge is an important source of firm performance. A host of studies in strategic management and industrial organization economics observed the expected positive relationship between technological knowledge and measures of sales or profitability (e.g., Chan *et al.*, 1990; Cockburn and Griliches, 1988; Ernst, 2001; Jaffe, 1986; Pakes, 1985; Wang, 2008; Woolridge and Snow, 1990). These earlier studies considered technological knowledge to be unidimensional and, therefore, examined the relation between quantity of knowledge and performance. However, scholars in the areas organizational learning and knowledge development (Henderson and Clark, 1990; Nonaka and von Krogh, 2009; Starbuck, 1992) by have persuasively argued that organizational effectiveness is more powerfully influenced by specific characteristics of knowledge stocks rather than just total quantity. Following that line of thought, we argue in this paper that, rather than total stock, depth and breadth of technological knowledge are important for firm performance. We test our hypotheses on a sample of manufacturing firms, using information embedded in patents to measure depth and breadth of technological knowledge.

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2. Literature review

2.1 Patents, technological knowledge and firm performance

Most of the fine-grained studies of antecedents and consequences of corporate technological knowledge have moved away from using R&D expenditure based measures. Instead, they use patent based measures arguing that patents, being outcomes of the knowledge development process, are more appropriate indices of technological knowledge. We review some of the noteworthy studies on antecedents and consequences of technological knowledge.

2.1.1 Antecedents. Studies in this stream focus on development of technological knowledge. They find that:

- firms where R&D is centralized tend to develop more diverse as well as more impactful technological knowledge (Argyres, 1996; Argyres and Silverman, 2004);
- quality of new technological knowledge created by a firm is affected by age of prior knowledge that the firm uses (Nerkar, 2003); and
- when specialization in different knowledge creation functions (generation, protection, utilization) is important, too little or too much integration across those three functions hinder technological knowledge creation (Reitzig and Puranam, 2009).

Studying factors affecting the successful development of technological knowledge is useful as it informs managers on effective strategy implementation. But what does research tell us about the performance consequences of corporate technological knowledge?

2.1.2 Consequences. Most studies looked at intermediate consequences, such as development of new products. They find that:

- to increase percentage of innovative new products, a firm should not only focus on developing both exploratory and exploitative knowledge but also time their development relative to its rivals (Katila and Chen, 2008);
- search and use of old technological knowledge facilitates a firm's product innovation so long as that knowledge is from external, not internal, sources (Katila, 2002); and
- a firm's existing knowledge and knowledge-creating capability affects its new product development (Smith *et al.*, 2005).

Product innovations are an intermediate consequence of technological knowledge. What about final consequences – i.e. corporate financial performance?

Patent-based studies have explored effects of (what we term) quality of a firm's technological knowledge. The number of times a patent is cited by subsequent patents could serve to index the impact (or quality) of the focal patent. A set of studies (Deng *et al.*, 1999; Narin *et al.*, 1987; Schoenecker and Swanson, 2002) provide some preliminary evidence that the ''current impact index'' of a firm's patents is positively related to its return on equity (ROE) and operating margins in chemical, electrical and pharmaceutical industries. However, effects of new technological knowledge on firm performance do not appear to be straightforward. Conducting a rigorous and fine-grained analysis, Heeley and Jacobson (2008) found that a firm's ROE (return on equity) was:

- negatively affected if a firm's new knowledge was based on technologies that are themselves new;
- positively affected if the firm's new technological knowledge was based on technologies that are not very novel; and
- negatively affected if the firm's new knowledge was a result of using old and well-established technologies, except when the old technology is used to develop products in a new market.

2.2 Knowledge management

The fundamental assertion of the resource-based view is that a firm's competitive advantage is a function of the degree to which its resources and capabilities are intangible and inimitable (Amit and Schoemaker, 1993; Grant, 1996; Petaraf and Bergen, 2003). One stream of theorizing posits that organization knowledge, consisting of marketing, technological and administrative knowledge, is an important resource in this regard. Such knowledge is the foundation of product/process innovations. Firms would, therefore, do well to develop and exploit knowledge resources. But what is it in organization knowledge that makes it intangible and inimitable? Much work has been done to answer this question and we summarize below some of the important studies.

The seminal work with regard to knowledge creation and exploitation of competitive advantage is that of Ikujiro Nonaka (Nonaka and Takeuchi, 1995; Nonaka and von Krogh, 2009), who portrays organizational knowledge as tacit knowledge shared by members of a firm through symbols and language unique to them and, thus, not easily deciphered by outsiders. Such tacit knowledge is made explicit in the form of new products and processes. Other studies (e.g., Allee, 2003; Heffner and Sharif, 2008; Mahesh and Suresh, 2009; Nerkar and Parachuri, 2005; Raider and Krackhardt, 2001) have built on this theme to analyze how networks hold organizational knowledge and what firms can do to facilitate network-based knowledge development and exploitation. Collectively, this work indicates that the intangibility and value of organizational knowledge lies in the fact that it is path-dependent, interactive, integrative, socially-complex, and that managers can design their firm's structure to exploit the value embedded in their knowledge stocks.

Despite its volume, there is a paucity of empirical investigation into the relationship between knowledge assets and performance. Moustaghfir (2008) conducted a systematic search in four major databases for scholarly articles related to knowledge management, and were published during 1985-2004. Of the 405 relevant articles he reviewed, only seven were related to performance effects of knowledge assets!

Our study addresses a gap in the above mentioned streams of research by conducting a fine-grained analysis of a firm's technological knowledge stock by disaggregating it into its depth and breadth components, and exploring their relation to financial performance. The few studies that have investigated these two dimensions of technological knowledge have looked only at pharmaceutical firms (Bierly and Chakrabarti, 1996; Subba Narasimha, 2001; Subba Narasimha *et al.*, 2003). In this study, we look at firms from a broad array of US manufacturing industries.

3. Theory and hypotheses

3.1 Concept of depth and breadth of technological knowledge

To state the obvious, innovations are tangible solutions (new products and services) to a problem. The new product or service is invariably an improvement over an existing product or service. Technological knowledge is input to the innovation process. The dominant view among innovation researchers is that:

- technological knowledge is the result of a search; and
- new knowledge is often times a recombination of existing or past knowledge (Dosi and Grazzi, 2006; Kogut and Zander, 1992).

So the question is how do (and should) firms search? There exist a wide variety of scientific and engineering disciplines. Thus, firms can search locally (in or near to their current areas of expertise) or distally (in technological disciplines not related to their current expertise. For purposes of our study, depth is the outcome of local search. Depth connotes ''analytical sophistication'' (Wang and von Tunzelmann, 2000). In contrast, breadth captures learning and search across technological disciplines. Given limited resources, firms are forced to choose the fields they will emphasize and to what degree.

Organizations can develop knowledge in a variety of technological domains. Because of limited resources, organizations are forced to make choices. By choosing to develop knowledge in one technological domain (or discipline), they reduce their options to develop expertise in other domains. Thus, an increase in knowledge in one technological field implies less knowledge in another field. Such choices profoundly influence an organization's ability to be successful in the long run. Hence, decisions regarding the depth and breadth become strategic questions. In the subsections below, we analyze the advantages and disadvantages related to continued emphasis of each dimension of technological knowledge, and develop testable hypotheses.

3.2 Varying usefulness of depth of technological knowledge

With respect to R&D, Nelson (1982) provides cogent arguments regarding the importance of ''deep learning''. R&D is fundamentally a process of searching among alternative pathways that are novel and uncertain. Such search is characterized by trial and error, false pathways, experimentation, and hits and misses. While neoclassical economists would have us believe that addition to existing knowledge is completely rational and independent of where the firm was on the knowledge pathway, notions of random walk would assert that it is completely random and fully path-dependent. Reality is in between – i.e. creation of new knowledge is a result of bounded (not pure) rationality as well as stumbling-into-it (Nerkar, 2003). The rational part has to do with the analytical sophistication a firm develops as it delves deeper into its current areas of expertise. Depth of scientific and technological knowledge makes the search process more efficient: the firm has a good understanding of the pitfalls associated with the alternative pathways; it knows what has worked (as well as not worked) in the past. Blind search is converted into a focused search. As a consequence one can expect a larger advance for a given outlay (Nelson, 1982). Firms build depth through exploitative learning (March, 1991), where search is localized to technological fields in which the firm is already active.

But there are limits to the returns a firm can expect from its local search (or continued enhancement of its knowledge in a specific technological discipline). Performance gains of any particular technological method exhibit a pattern of decreasing gains (Dosi, 1982). For example, in semiconductors, speed of transfer is achieved by decreasing the distance between the devices that electrons have to travel. But there is a limit to how much the distance can be reduced. Reduction beyond a stage results in instability of the devices' performance (Coombs, 1988). The above arguments lead to the following hypothesis:

H1. Strength of the positive relationship between depth of technological knowledge and performance initially increases and later decreases.

3.3 Varying usefulness of breadth of technological knowledge

Both technological and product imperatives require firms to maintain some degree of breadth of knowledge – i.e. knowledge of multiple technological disciplines. Technological imperatives arise from the fact that many technologies face competing technologies. Often, a desired outcome can be achieved using more than one technological method (Arthur, 1988). The rate of knowledge accumulation and, hence, progress of the competing technologies differ. Thus, a technologically and economically inferior method may surpass the dominant technology and render it obsolete. Secondly, if a firm has to overcome diminishing returns to movement along the specific technological trajectory that it is on, the firm needs to jump to a different ''technological paradigm'' (Dosi, 1982) – from, say, vacuum tubes paradigm to transistors paradigm. This calls for exploratory learning. While risks may be high because of novelty, returns could also be high (March, 1991). Finally, a straightforward way to increase the chance of success when operating under high uncertainty is to broaden the categories of technological knowledge that a firm pursues (Leiponen and Helfat, 2009).

Product imperatives calling for breadth of technological knowledge arise because of product complexity. Often, products require knowledge of a variety of scientific and engineering areas (Ernst, 2001; Granstrand *et al.*, 1997). Firms often deal with this situation by developing core technologies in house and obtaining the remaining technologies through licensing or strategic alliances. However, this does not mean that the firm can remain completely ignorant of those technologies. It needs to have adequate understanding of how the other technologies interact and integrate with its own core technologies (Brusoni *et al.*, 2001; Henderson and Clark, 1990). Hence, to be assured of long-term success firms need to maintain a certain breadth of technological knowledge.

As in the case of depth, we can expect decreasing performance returns to breadth of technological knowledge. There are limits to a firm's information processing capability. More importantly, the variety of information to be processed and recombined also increases because of differences in nature and type of information. As a result, we can expect diseconomies of information processing to become salient as costs of integrating knowledge from disparate technological disciplines exceed their benefits (Fleming and Sorenson, 2001). Thus, the following hypothesis:

> *H2.* Strength of the positive relationship between breadth of technological knowledge and performance initially increases and later decreases.

3.4 Interactive effects of depth and breadth of technological knowledge

H1 and *H2* focus on performance effects of one component of technological knowledge independent of the other component. In actuality, the components are not loosely-coupled. Very often, they are interwoven, with each component acting to enhance the role of the other component. Hence, we can expect to observe joint effects as well. Thus, the hypothesis:

> *H3.* Depth and breadth of technological knowledge have interactive effects on firm performance.

4. Method

4.1 Sample

Data for the study come from five different sources: US Patent Office, to help calculate the technological knowledge variables; COMPUSTAT and the National Bureau of Economic Research R&D Master Data Tape (Cummins *et al.*, 1985) to calculate firm performance; Yale Industrial R&D Study (Yale Survey, 1983) to calculate propensity to patent; and US Census of Manufactures to calculate industry concentration and market growth.

Availability of data dictated the use of variables in the statistical analysis. Obtaining patent statistics for firms by the technology classes was the most difficult. As these data were available for just the 1973-1979 time period, all other information had to be collected for that period. When data from the various sources were merged, the sample size containing no missing values was 278. This number reduces to 73 because of the three steps we took to increase reliability of the results. One, all financial numbers were adjusted for inflation. Two, only firms with valid performance data for at least five of the seven years (1973-1979) were selected for study. Three, only firms with high propensity to patent were selected. Patents capture only articulable knowledge that has been articulated (Winter, 1987). If propensity to patent is low, patents are incomplete indices of knowledge. A propensity to patent index was calculated for each firm using a survey item from the Yale Survey data. The survey conducted in 1983 asked respondents about the degree (on a seven-point Likert scale) to which patents are effective in preventing innovations from being duplicated by rivals (Yale Survey, 1983). A high score implies the firm's propensity to patent will be high. Using that score for this study's sample firms, a subsample was formed of firms with a propensity to patent score greater than 4.00. The set of 73 firms so selected form the sample for analyses here.

4.2 Measures

4.2.1 Dependent variables. Three different performance indicators were used in the analysis: accounting profitability, sales growth and Tobin's *q*. Instead of choosing a particular dimension, it was decided to explore the relationship of technological knowledge to all three dimensions:

1. *Return on invested capital.* This index was used as a measure of accounting profitability. Return on Invested Capital rather than return on equity was chosen as the latter suffers from distortion due to inter firm differences in debt-equity ratio. Return on Invested Capital was measured as: INC + DEP + INT/GCAP, where: INC = income before extraordinary items and discontinued operations, DEP = depreciation, INT = interest income, and GCAP = gross book value of plant + inventories + investments in unconsolidated subsidiaries.
2. *Sales growth.* Sales growth was measured as: (100/6) * [$\text{Sales}_{1979} - \text{Sales}_{1973}$]/$\text{Sales}_{1973}$.
3. *Tobin's* q. Tobin's *q*, defined as the ratio of a firm's market to its replacement value, has been argued to be more accurate than pure accounting- or market-based measures at capturing economic rents.

Accounting-based measures have been criticized as they:

- provide no information on economic rates of returns;
- do not take systematic risk into account;
- are distorted by tax laws and arbitrary accounting conventions; and
- distort inter-firm comparisons because larger firms and regulated firms tend to choose accounting methods that systematically understate profits (Fisher and McGowan, 1983; Smirlock *et al.*, 1984).

Tobin's has the advantage of being able to:

- index long-run monopoly power;
- incorporate firm earnings risk; and
- minimize distortions due to tax laws.

Tobin's *q* was calculated for each of the years 1973-1979 and averaged.

Data for both the numerator and denominator of Tobin's *q* were obtained from the R&D Master File of the National Bureau of Economic Research. Details of construction of the variables provided below are taken from Cummins *et al.* (1985).

Market value was calculated as the sum of the values of:

- common stock (year-end value);
- preferred stock (computed as preferred dividends paid during the year by the firm divided by Moody's preferred dividend rate for medium risk companies);
- current liabilities (valued at book) less value of net short-term assets (calculated as Current Assets − Book Value of Inventories − Current Liabilities + Debt in Current Liabilities); and
- long-term debt (calculated on the assumption that all bonds have a 20 year maturity and offer a yield calculated from Moody's corporate BAA bond price series).

The replacement value of physical assets was calculated as the sum of replacement values of:

- plant and equipment;
- inventory; and
- other assets.

The net value of plant and equipment was calculated by multiplying the book value by the ratio of the GNP deflator for fixed non-residential investment for the current year to that *x* years ago – where *x* is the average age of the firm's plant and equipment. The average age series was calculated as the ratio of accumulated depreciation to current year's depreciation assuming a straight-line depreciation. Inventories were adjusted for inflation using the inventory price index. Other assets, consisting of investments in unconsolidated subsidiaries and other intangibles, were adjusted for inflation using the same procedure as for the inventory adjustment. The deflator for fixed residential investment was used for the adjustment factor.

4.2.2 Independent variables. Depth and breadth of technological knowledge. Patents appear to be the most feasible way for operationalizing these two dimensions of technological knowledge. The Patent and Trademark Office has constructed an elaborate classification scheme consisting of 352 different classes of technology (US Department of Commerce, 1986). Each class represents a particular scientific or engineering field. When a patent is granted, the technology class to which it belongs is noted on the patent document. This information helps construct the depth and breadth measures.

We follow Jose *et al.* (1986) to develop our depth and breadth measures. Suppose a firm's total number of patents is distributed over *n* patent classes. Let *p* be the fraction of patents that are in patent class *i*. Then a measure of technological knowledge diversity TK_{div} is, $TK_{div} = 1 - \Sigma p_i^2$. This Herfindahl-type index ranges from 0 at the lower end (implying technological knowledge in a single class) to a theoretical maximum of 1 (implying technological knowledge spread over a wide range of classes). A shortcoming of the measure is that it does not provide any indication of the spread of patents across patent classes. The measure can be modified to overcome that lacuna. Adding and subtracting $1/n$ to the Herfindahl-type index yields, $TK_{div} = (1 - 1/n) - \Sigma[p_i^2 - (1/n)^2]$, i.e. $TK_{div} = TKb - TKd$, where TKb is breadth of Technological Knowledge and TKd depth of Technological Knowledge. The first term is bound by 0 and 1. As '*n*', the number of technology class increases, the term increases thus capturing breadth of a firm's technological knowledge. The second term also varies from 0 to 1. For the same degree of breadth, values of the depth component increases as patents become increasingly concentrated in a small number of technology classes. If the patents are equally distributed across technology classes, the depth component takes a 0 value. Increasing values of the component imply an increasing asymmetry in the distribution of patents across technology classes. Thus depth captures the degree to which a firm shuns dispersal of its knowledge, preferring instead to be more knowledgeable in a smaller number of technology classes. We calculated depth and breadth of technological knowledge for our sample firms using the formulae above. Technology class information was not on available on a yearly basis. Rather, we have it in an aggregated form for the 1973-1979 period.

Control variables. Both industry and firm factors affect performance. It has been argued that industry concentration and market growth affect firm performance (Salinger, 1984; Smirlock *et al.*, 1984). Hence, Concentration (CONC) and Market Growth (MGWTH), measured using the 1978 four-firm concentration ratio and average annual growth in industry value of shipments between the years 1973 and 1978, were introduced as controls into the analyses. For diversified firms in the sample, weighted averages were calculated with the percentage of total firm sales accounted for by each line of business serving as the weight.

In addition to the industry variables, a variable indexing the total stock of technological knowledge was also introduced as a control. In fact, the main contention of this paper is that depth and breadth of technological knowledge are more powerful explanators of performance than is total stock. The variable, R&D Capital Stock (RNDSTK), was calculated as the cumulative sum of R&D investments during the 1973-1979 period. Intangible stocks are subject to depreciation just like tangible assets, and needs to be taken into account when calculating R&D capital stock. Following earlier studies (Grabowski and Mueller, 1978; Salinger, 1984), the yearly R&D investments were depreciated at a ten percent rate assuming a constant proportional rate of depreciation.

4.3 Analyses

Hierarchical regression models are the most appropriate for testing this study's hypotheses. The regression equation is:

$$\begin{aligned} \text{Performance} = {} & a_0 + a_1\text{CONC} + a_2\text{MGWTH} + a_3\text{RNDSTK} + a_4\text{TKd} + a_5\text{TKb} \\ & + a_6(\text{TKd})^2 + a_7(\text{TKb})^2 + a_8\text{TKd}^*\text{TKb} \qquad (1) \end{aligned}$$

where, CONC is industry concentration, MGWTH is market growth, RNDSTK is R&D Capital

Stock, TKd is Depth of Technological Knowledge, and TKb is Breadth of Technological Knowledge. Three separate regressions need to be performed – one for each of the three performance measures of Return on Invested Capital, Sales Growth and Tobin's *q*.

Introduction of quadratic and cross-product terms could very well result in high multicollinearity. Replacing the raw scores of the depth and breadth variables by deviations from their means helps reduce multicollinearity (Smith and Sasaki, 1979). We used condtion indices to find out if there is a need to take remedial measures for multicollinearity problems. As a result of using transformed variables for depth and breadth of technological knowledge, the condition index values decreased to 18 or below indicating that there was no need to take any remedial action (Belsley *et al.*, 1980). Thus, we ran ordinary least square regressions, and use unstandardized regression coefficients for analyses and interpretation of results.

4.4 Results

4.4.1 Sample statistics. The sample of 73 firms used for the study is quite diverse representing a total of 14 different two-digit SIC industries. Annual sales of our sample firms range from $3 million to $10.5 billion with an average of $1 billion; total patents from 15 to 1,751; with the patents spanning from a minimum of 5 to a maximum of 120 different technology disciplines. These statistics attest to the wide range of firms in the sample (see Table I).

4.4.2 Regression results. Table II provides results of our regression analysis. We highlight the results in two ways; first by looking at the whether or not the hypotheses are supported, and, second, by focusing on the nature of effects of depth and breadth on each of the three performance variables.

With respect to our hypotheses, there are five noteworthy aspects. One, R&D Capital Stock is statistically insignificant in the case of all three performance measures. This implies that total stock of technological knowledge loses its explanatory power when we introduce the finer measures of depth and breadth of Technological Knowledge.

Two, on the whole, depth and breadth of Technological Knowledge do affect firm performance. R^2 and Incremental R^2 numbers (last four rows of Table II) provide an indication of their strength. For example, in the case of Return on Invested Capital, 48 percent of its variance ($R^2 = 0.48$) is explained by the full model. Of that total explained variance, incremental R^2 indicates the amount explained by the depth and breadth variables – which is 0.25. Thus, more than half of the explained variance of Return on Invested Capital (0.25/0.48) is accounted for by depth and breadth of Technological Knowledge.

Three, depth of Technological Knowledge has non-linear effects on two of the performance variables – Return on Invested Capital and Sales Growth. However, the linear terms (-6.83 for Return on Invested Capital and -9.08 for Sales Growth) are negative, and the squared terms (1.55 and 2.67) are positive suggesting that the depth-performance relation is negative initially and turns positive at higher levels of depth. This is opposite to that expected in hypothesis *H1* which predicted an inverted-U relation between depth of Technological Knowledge and performance. Thus, although the results do not support hypothesis *H1*, they support a significant expectation of ours – that the effects of depth of Technological Knowledge are non-linear.

Four, results do not support hypothesis *H2* regarding performance effects of breadth of Technological Knowledge. In the case of Return on Invested Capital and Tobin's *q*, neither linear (-4.84 and -93.36 respectively) nor squared terms (2.30 and 44.16 respectively) are statistically significant, indicating that breadth of knowledge has no effects. In contrast, results show that it does affect Sales Growth, although the direction of effects is opposite to that predicted. If hypothesis *H2* were correct the coefficient of the linear term should be positive and that of the squared term negative. Results are the opposite: -17.9 and $+9.7$ for the linear and squared terms.

Table I Sample statistics and Pearson zero-order correlations ($n = 74$)

	Mean	*SD*	*Min.*	*Max.*	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. Return on invested capital	0.08	0.07	−0.41	0.19	1.00						
2. Sales growth	0.04	0.06	−0.12	0.18	0.47****	1.00					
3. Tobin's q	1.20	1.01	0.27	4.51	0.84****	0.44	1.00				
4. Concentration	0.38	0.11	0.18	0.79	−0.34**	−0.23*	−0.34***	1.00			
5. Market growth	0.23	0.16	0.03	0.81	0.09	0.20*	0.02	−0.23*	1.00		
6. R&D capital stock	3.53	1.59	−2.17	6.47	0.16	0.15	0.34***	0.23*	−0.12	1.00	
7. Technological knowledge (depth)	0.10	0.07	0.01	0.48	0.32***	0.25**	0.40****	−0.32***	0.38****	−0.06	1.00
8. Technological knowledge (breadth)	0.95	0.04	0.80	0.99	0.03	0.15	0.12	0.21*	−0.21*	0.71****	−0.46****
Additional descriptive statistics											
1. Total patents	296		15	1,751							
2. No. of technological classes	39		5	120							
3. Average annual sales (in millions of US dollars)	1,241		3	10,591							

Notes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$; $^{****}p < 0.001$

Table II Regression results[a] ($n = 73$)

	Performance variable 1 Return on invested capital	2 Sales growth	3 Tobin's q
Concentration	−0.04	−0.02	−1.78*
Market growth	0.03	0.07	−0.15
R&D capital stock	0.00	−0.01	0.16
Technological knowledge (depth)	−6.83****	−9.08**	−138.74**
Technological knowledge (breadth)	−4.84	−17.90**	−93.36
[Technological knowledge (depth)]^2	1.55**	2.67**	29.67
[Technological knowledge (breadth)]^2	2.30	9.70**	44.16
Technological knowledge (Dp) × Technological knowledge (Br)	7.15****	9.38**	149.10***
Constant	2.60****	8.30****	49.62****
R^2	0.48****	0.29***	0.55****
Adj. R^2	0.41	0.20	0.50
F	7.27	3.32	9.86
Incremental R^{2b}	0.25****	0.09**	0.16***

Notes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$; ****$p < 0.001$; [a]Unstandardized coefficients are provided; [b]Value is for the quadratic and interaction terms, which were entered last in the hierarchical regression

Five, hypothesis *H3* about the interactive effects of depth and breadth is supported for all three performance measures. Consistently across all three performance variables, we see the direct effects of depth are negative (−6.83, −9.08, −138.74) and the interactive effects of depth and breadth are positive (7.15, 9.38, and 149.10) and statistically significant. However, results show differences as well. We focus on the nature of effects of depth and breadth on each performance variable next.

4.4.3 Results for return on invested capital – Table I column 1. The breadth component has neither linear nor quadratic (*H2*) effects. The depth component's statistically significant negative value for the linear term (−6.83) and positive value for the quadratic term (1.55) imply a negative relationship for low depth that changes to positive values as depth increases. Within the range of depth values that are to be found in the sample (0.01 to 0.48), the relation of depth to Return on Invested Capital remains negative. It is the enhancing role of breadth that catches attention here. To understand the facilitating role of breadth, we start by taking the partial derivative of equation (1) with respect to TKd and substituting values from Column 1 of Table II:

$$\frac{\delta(\text{Return on Invested Capital})}{\delta(\text{TKd})} = -6.83 + 1.55{*}2{*}\text{TKd} + 7.15{*}\text{TKb}. \qquad (2)$$

The point at which this partial derivative becomes zero is the point at which Return on Invested Capital (as a function of TKd) goes from negative to positive. Setting the partial derivative to 0 allows us to find the values at which Return on Invested Capital as a function of TKd makes the transition. The presence of TKb in the partial derivative means that the transition point is a function of TKb. We will call this value the "positive contribution point" for TKd for each different value of TKb. Alternatively:

$$\text{TKd} = \frac{6.83 - 7.15{*}\text{TKb}}{3.1}. \qquad (3)$$

Thus, as TKb increases the positive contribution point of TKd decreases – i.e. contributions to Return on Invested Capital becomes positive at smaller values of depth of technological knowledge.

Proceeding in a similar manner, we may look at what happens to breadth's positive contribution point as a function of TKd. We derive:

$$\frac{\delta(\text{Return on Invested Capital})}{\delta(\text{TKb})} = -4.84 + 2.3{*}2{*}\text{TKb} + 7.15{*}\text{TKd}. \quad (4)$$

Setting this partial to 0 and solving for TKb, we get:

$$\text{TKb} = \frac{4.84 - 7.15{*}\text{TKd}}{4.6}. \quad (5)$$

Thus, we see that as TKd increases the positive contribution point for TKb gets smaller.

Because of the symmetry of the independent variables (first order coefficients are negative and second order coefficients are positive), results for Sales Growth and Tobin's *q* will be similar.

4.4.4 Results for sales growth – Table II column 2. The significance of this performance variable's results is that linear and quadratic terms of both depth and breadth are statistically significant. Signs of the various terms are the same as in the Return on Invested Capital model. Findings for depth there apply here for both depth and breadth.

4.4.5 Results for Tobin's q *– Table II column 3*. The pattern of relations between Tobin's *q* and depth and breadth of technological knowledge are similar to those seen for Return on Invested Capital. One difference is as the depth component's quadratic term is not significant perhaps because of presence of the other knowledge terms – i.e. TKb, TKb^2 and TKd*TKb. To provide additional clarity on the pattern of relations between depth, breadth, and Tobin's *q*, we add an additional layer of detail to the partial derivative analysis.

The partial derivative with respect to depth is:

$$\frac{\delta(\text{Tq})}{\delta(\text{TKd})} = -138.7 + 29.67{*}2{*}\text{TKd} + 149.1{*}\text{TKb}. \quad (6)$$

Fixing TKd to its minimum, mean and maximum values (0.01, 0.10, and 0.49), and solving for TKb yields three points: 0.93, 0.89 and 0.74. What do they mean? Let us take the middle case: the positive contribution point of depth is 0.10 when breadth's value is 0.89. That is, below 0.1, an increase in depth results in a decrease in Tobin's *q,* and above 0.1 increases in depth lead to increases in Tobin's *q*. Stated differently, when breadth is 0.89 the depth – Tobin's *q* relation is non-linear being negative for values of depth below 0.10 and positive above 0.10. What if we want the relation to be positive for lower levels of depth, say 0.01? Then breadth has to be increased to 0.93. This illustrates what was said earlier for Return on Invested Capital – that as TKb increases the positive contribution point for TKd gets smaller.

To get a visual image of the nature of relations between depth, breadth and Tobin's *q*, we have graphed them in Figures 1 and 2. The three panels in Figure 1 show variation in Tobin's *q* as a function of depth at three different levels of breadth – 0.80 (minimum for the sample), 0.90 (mid of the range) and 0.99 (maximum for the sample). The top panel indicates that when breadth of technological knowledge is low, increases in depth of technological knowledge initially decreases and then increases performance. It is only when breadth has moderate to high values (i.e. above 0.93) that performance increases over the whole range of depth of technological knowledge – shown in the middle and bottom panels of Figure 1.

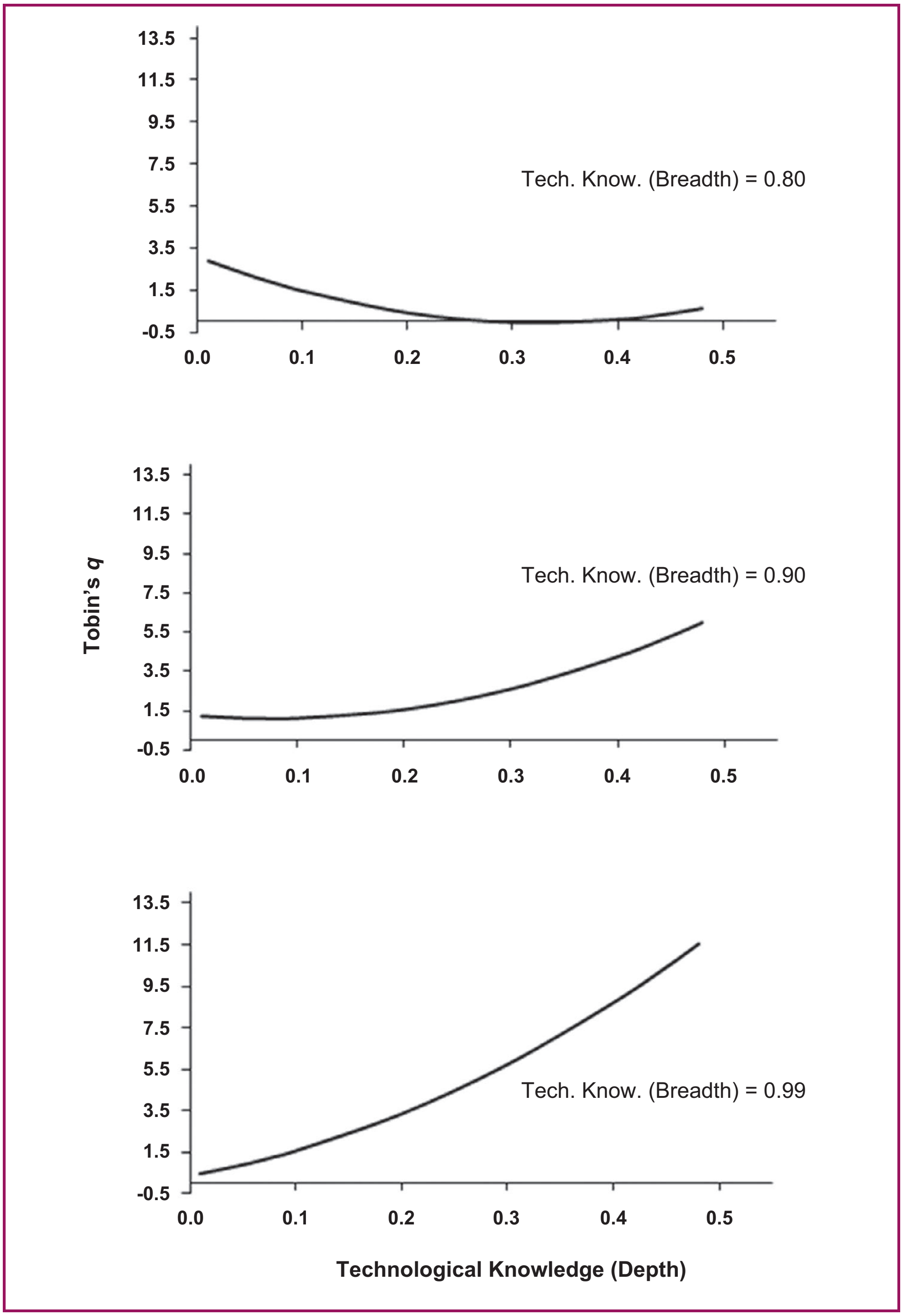
Figure 2 depicts the breadth – Tobin's *q* relation at three different levels of depth – at its minimum (0.01) mean (0.10) and maximum (0.48). We see the pattern is quite similar to that in Figure 1.

4.5 Summary of results

Our study has four important findings:

1. Total stock of technological knowledge is not as important an explanator of firm performance as its constituent depth and breadth components.

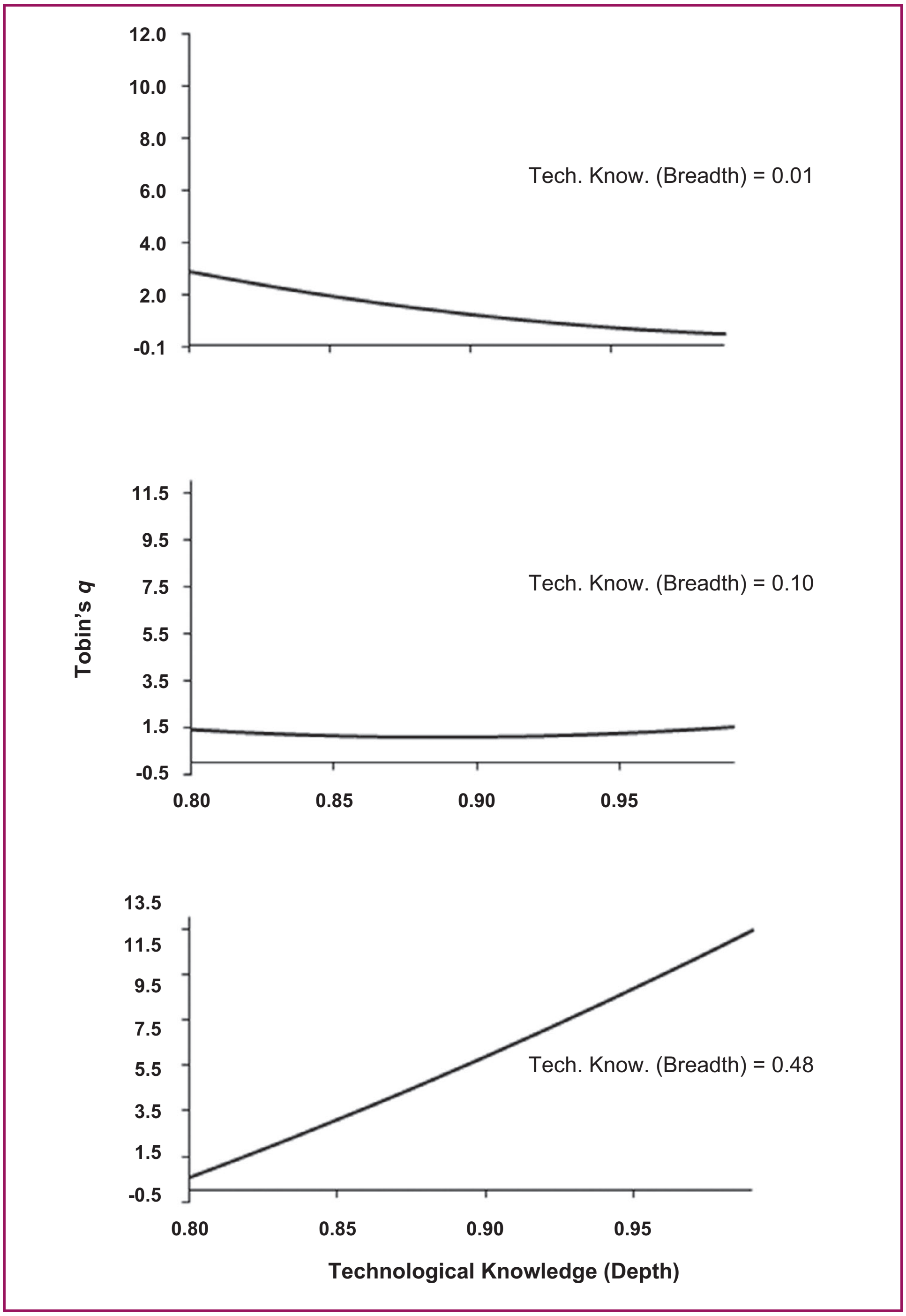
Figure 1 Variation in Tobin's *q* as a function of depth of technological knowledge



2. While there are some differences in the nature of effects that depth and breadth of technological knowledge have on Return on Invested Capital, Sales Growth, and Tobin's *q*, the basic result is that depth and breadth have non-monotonic effects on the three performance measures.

3. Contrary to hypothesis *H1*, performance initially decreases as depth of technological knowledge increases i.e. the curvilinearity of depth-performance relation is concave rather than convex.

Figure 2 Variation in Tobin's *q* as a function of breadth of technological knowledge



4. The positive and statistically significant interaction terms for all three performance cases (7.15, 9.38, and 149.10) shows their facilitating nature. As one component grows the other component has a positive contribution point at smaller and smaller values.

5. Discussion

We discuss three aspects of our study's results. First, using Sales Growth as guide we consider the relationship between depth and breadth of knowledge. Second, we give some thought to our study's reliability and generalizability. Third, we consider implications for further research and for practitioners.

5.1 Explaining the relationship between performance and knowledge

We developed our hypotheses based on an economic model of diminishing marginal returns. It appears that may not be the best model, at least for the variables included in this study. We observe, most clearly in the case of Sales Growth, that each of depth and breadth moved from a negative impact to positive influence. More specifically, if one variable (say breadth of technological knowledge) is held constant, then the other variable (depth of technological knowledge) negatively affects performance at lower values and has positive effects only when it is increased. We postulate some possible explanations for this transition.

5.1.1 The minimum requirement explanation. For technological knowledge to have a positive effect, firms need to have a minimum amount of it. That is, there needs to be a threshold level of knowledge and learning of a particular technological discipline. Deep understanding requires more than scratching the surface. Start up costs is involved as firms need to delve deeper. In our sample, depth ranges from a minimum of 0.01 to a maximum of 0.48. In the lower range of values, the firm simply does not have enough expertise or experience to effectively apply its knowledge to create new products or services. Hence the observed 'U' curve.

5.1.2 The complex technological environment explanation. This explanation focuses on the increasingly fast rate of technological change on the one hand, and increasing sophistication and quality of products on the other. This explains the fact that firms, at least the large ones, are increasing their technological diversity at the same time that they may be narrowing their product lines. Such is the case in aircraft engine control systems (Brusoni *et al.* 2001), and in electronics and food-processing industries (von Tunzelmann, 1998). More broadly, Granstrand *et al.* (1997) found the same pattern, of narrow products lines and increasing technological diversity, in their study of 440 most technologically active companies in the world.

5.2 Reliability and generalizability

How reliable are this study's results? Given our elaborate sample selection process, reliability should be moderately high. Our measures capture only explicit knowledge. Reliability is affected to the degree tacit knowledge affects firm performance. If tacit knowledge aids explicit knowledge then strength of the observed relations would be understated. This is of less concern as it means the study's findings are supported. On the other hand, it would be a concern if tacit knowledge changed the direction of relations between depth/breadth of technological knowledge and performance. In such a case reliability would be low.

How generalizable are our results? Not very broadly. One, the findings are restricted to manufacturing firms, and do not extend to software and IT consulting firms (where knowledge management is of utmost importance). Two, we restricted our sample to firms whose patenting propensity is high. It helped increase reliability, but resulted in decreased generalizability.

5.2.1 Implications for research. Our study's primary contribution is to the stream of work in resource-based and organizational-knowledge perspectives of firm behavior. Our results emphasize the importance of further study of the effects of depth and breadth of technological resources on competitive advantage. Further study should investigate more recent time periods, longitudinal effects, and expand consideration of underlying forces that drive the independent variables.

The strong interaction effects (and quadratic effects for Sales Growth) suggest, not surprisingly, that the situation is not as simple as a linear model would suggest. The patent variables are snapshots of complex research and human interaction that underlies the patenting process. One first step in investigating further would be to collect and analyze longitudinal data on depth and breadth of technological knowledge over time to better understand the temporal relationship of these variables to firm performance.

Because of the importance of the variables, further study should investigate the underlying knowledge generation processes leading to patents in more detail. These processes are likely to interact with each other and create path-dependent outcomes. Complexity theory provides one useful conceptual basis for such study. Perspectives in the field of complexity view an entity (the firm in our case) as a system of interactive parts with each part changing over time following simple rules. As the parts are interdependent, their interactive effects over time lead to outcomes that are nonlinear in nature. Complexity scholars look at a system:

- focusing on its dynamics rather than on stability;
- emphasizing its openness to its surroundings (landscape); and
- capable of adapting (i.e. evolving) by means of organizing itself through complex interactions among its parts (Teisman and Klijn, 2008).

Morris Holbrook points out that ''A business (can be) regarded as a dynamic open complex adaptive system (DOCAS), composed of inter-related parts, interacting with its environment, subject to resulting feedback effects, evolving over time adaptively to fit the pressures imposed on it, perhaps attaining a sustainable advantage . . . (Holbrook, 2003, pp. 1-2). Two excellent examples of how complexity theory can be applied to business settings are those of Losada and Heaphy (2004), who studied how dynamic (and evolving) interactions among members of a team affected subsequent performance of their team; and Burgelman and Grove's (2007) study of strategy making at Intel.

5.2.2 Implications for practitioners. On the one hand, a traditional view of our efforts might suggest the work of corporate strategic planners be expanded by asking them to add two additional meters to their balanced scorecards (Kaplan and Norton, 1996). The strength of the effects of breadth and depth, as well as the variation in effects of each, show how important it is to keep track of the breadth and depth combination. Planners then might use the formulae developed here to measure the breadth and depth of their firm's technological knowledge stocks. They should gather such data for the past five to seven years. Such longitudinal data would help examine the change in patterns of both technological knowledge and performance, and notice whether their firm's performance is inferior (or declining) when ever breadth and depth combinations are skewed – i.e. very high or low on one of the two dimensions. Finally, planners can decide if their industry and technology contexts require skewed breadth and depth combinations. If they do not, planners should take steps to achieve a more balanced combination of the two dimensions.

On the other hand, a daring view of our research suggests the importance of a deeper understanding of the roles of breadth and depth of knowledge. It underscores the need to understand the complexity of the organizational processes underlying knowledge creation. Practitioners need to become familiar with the implications of complexity theory as a means of understanding the situation. There are many ways of examining and incorporating complexity research into the practitioner's tool kit.

One approach is to recognize that complex dynamic systems can generate emergent macro forms from the predictable interaction of micro actors. This suggests that modeling of micro behavior might lead to practical models of the knowledge creation process and particularly the process of creating patents. This information can then be used to build and refine models, and perform simulations to better understand the way knowledge is built in the practitioner's firm and industry.

A second, and more radical approach, is to recognize that the underlying complexity is the result of the interaction of heterogeneous agents who recreate their environments through their continued interaction. Emergent patterns of innovative action then come from the individual interactions and are largely independent of management direction. Detailed descriptions of how knowledge might emerge in tangible form from these interactions are beyond the scope of this paper but have begun to be explored in the literature applying complexity to organizations. Ralph Stacey (2007) provides one such exploration providing a detailed review in a business strategy setting.

6. Conclusion

The study's findings are encouraging. Its results clearly indicate that firms need to pay attention to their technological knowledge stocks. As argued earlier, complexity theory could be of help in investigating the interactive effects of different technological knowledge dimensions. There is equally well a need to broaden the scope investigation beyond technology. Obtaining and sustaining a firm's competitive advantage needs more than just technological competence. In many, if not all, industries marketing competence is equally important. Marketing scholars posit that a firm's ''market orientation'' is an important determinant of performance (Kirca *et al.*, 2005). A study of 748 firms spread across a wide variety of industries found that a firm's ''market orientation'' and ''marketing capabilities'' affected its return on investment (Morgan *et al.*, 2009). While there exist a host of studies looking into the performance effects of one specific competence (or resource), very few have examined effects of two or more resources (Newbert, 2007). A fruitful line of inquiry would, therefore, focus on both technological and marketing competencies. Such studies should be carefully crafted to investigate both independent and complementary effects of the two resources on performance.

As the resource-based perspective cautions us, resources, in and of themselves, do not assure a sustainable competitive advantage. Firms need capabilities to convert their resources into useful products/services (Teece *et al.*, 1997). Human resource practices and organization structuring are important in this regard (de Pablos and Lytras, 2008; Danskin *et al.*, 2005). Investigations of how these two capabilities moderate (or mediate) the technological knowledge-performance relation would yield rich dividends, especially to practicing managers.

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