R&D, Information Technology, and Firm Performance: A Complementarity Model

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1. Introduction

Technological change is an important determinant of productivity growth and increases in the economic standards of living over time. Technological change occurs as a result of *innovation* which is defined as "activities involved in inventing new products and processes, improving existing products, processes or services, and reducing the cost of producing existing goods and services" (Congressional Budget Office Report, 2005). Research & development (R&D) is a key component of innovation and refers to activities that help develop new knowledge, products, and devising better ways of developing new products and/or services. The business press provides numerous examples of the importance of the R&D as a driver of innovation that result in new discoveries, products and/or services (Jaruzelski et al. 2005; Kandybin and Kihn, 2004). A large number of academic studies have also focused on the relationship between R&D spending, productivity growth, and firm-level performance (Morbey, 1988; Cohen and Klepper, 1996; Ettlie, 1998; Cohen, Levin and Mowery, 1987). While earlier studies on R&D spending reported that R&D's effect on firm productivity was not statistically significant, recent studies suggest that R&D spending has a significantly positive impact on productivity growth, with a rate of return that is somewhat larger that the rate of return on conventional investments (Lev and Sougiannis, 1996; Chan, Lakonishok and Sougiannis, 2001).

The mixed evidence of the impact of R&D on firm performance brings to mind new questions. Is R&D alone a sufficient determinant to explain the firm performance? Could there be other factors that moderate the impact of R&D? Johnson and Pazderka (1993) argue that R&D spending is a noisy measure of innovative activity from the perspective that different models and data sets are needed to confirm the impact.

One company investment that could play an important enabling role in the execution of innovation-intensive processes is information technology (IT). Field studies and emerging empirical data on the role of IT (by us and other authors) point to the potentials and pitfalls of applying IT for improved enterprise performance. In a recent study by McKinsey, Marwaha et al. (2007) observe that pharmaceutical companies which use IT in clinical trials processes increased their overall productivity by improving the speed, quality and the costs associated with these processes. Estimated savings from such IT-driven initiatives that improve the overall efficiency of clinical trials is estimated to be in the range of $50 million to $100 million. Others in the popular and managerial press have written about the limited role of IT in improving enterprise effectiveness and creating business value (Carr, 2004). However, there does not exist much research how IT investments interact with R&D investments in the enhancement of firm performance.

We study the role of IT in influencing the impact of R&D investments on firm performance. We formulate an analytical model through which we derive and then test our research hypotheses on a unique data set of firm-level post-Internet R&D and IT spending based on a recent data set (1998 to 2004) that allows us to study the impact of web-based IT investments. To the best of our knowledge, this study is the first attempt at examining the joint impact of R&D and IT on firm performance using recently available data that allows us to study the profitability impact of newer technologies at the firm level.

Our results indicate that sales-normalized IT spending moderates the impact of sales-normalized R&D spending on two measures of overall firm performance: *gross margin*, which serves as a proxy for profitability, and *patent count*, which serves as a measure of new innovation. However, our analyses suggest that these effects are not observed across the board for all types of firms. Rather, the effects are more *nuanced* depending on a firm's relative spending within its industry and the type of cost structure the firm faces Our results indicate that the overall impact of R&D and IT spending is greater among firms in knowledge-intensive industries such as Pharmaceuticals and high technology with more of a fixed-cost intensive business model than in the industrials sector with a higher variable cost structure.

Next, we review the literature on R&D and IT-enabled innovation and propose a framework for studying the role of IT in moderating the impact of R&D with the help of a case study in the bio-pharmaceuticals sector. In the following section, we develop our research hypotheses using a simple analytical model and propose a conceptual research model to describe the focus of our study. We then describe our research data followed by our econometric estimation section. We conclude with a summary of the key findings of our research and its implications for future research.

2. Related Literature

There exists a fairly large amount of literature on the impact of R&D on productivity and firm performance. However, much of this literature does not consider the role of IT investments (Griliches and Mairesse, 1984; Englander, Evenson, and Hanazaki, 1988; Chauvin and Hirschey, 1993; Griliches, 1994; Lee and Shim, 1995; Hall and Mairesse, 1995). We now review the literature on the impact of R&D and IT investments on firm productivity and performance as a prelude to developing a theory-based model which we test using data.

2.1 Role of R&D Investments

The quest for innovation has long been considered a silver bullet to improve firm performance through sales growth and increased profitability. R&D spending has been a subject of much attention especially with the growth of science- and technology-based industries that are active in R&D during the last two decades. The high technology and pharmaceuticals industries together account for more than a third of the market value of the Standard and Poor (S&P) index. This rise in importance of knowledge-intensive industries raises the question of whether their performance accurately reflects the investments in R&D capital. In other words, does R&D contribute to growth in firm profitability and innovation?

Several studies, both in the academic and practitioner literature, have studied the relationship between R&D investments and firm performance. While most studies have focused on the impact of R&D spending on firm productivity growth, a few have explored the relationship between R&D and financial and accounting measures of firm performance, such as stock price/market value, and operating income. Although early studies reported that the effect of R&D on productivity is not significantly different from zero, more recent studies have found that R&D's effect is substantially positive and significantly exceeds that of other discretionary investments (CBO Report, 2005; Lev and Sougiannis, 1996). Although the consensus view is that R&D has a positive impact on productivity, limitations associated with the available data and variety of estimation methods used make it difficult to establish a precise magnitude of this impact. Hence, the estimates of R&D elasticity vary widely depending on the sample, time period, and estimation methods used.

A review of the R&D productivity literature suggests that there is a divergence between cross-sectional and longitudinal, time-series estimates. The strongest results, in terms of R&D impact, are reported in the cross-sectional studies, whereas time-series studies that link R&D to total factor productivity (TFP) growth produce weaker results with some studies that show statistically insignificant estimates. Other limitations in terms of developing accurate estimates of the impact of R&D can be summarized as: (a) evidence of spillovers where the benefits accrue to firms or nations other than the ones making these investments, and (b) focus mostly on private R&D spending based on financial data reported by publicly traded firms, which reflects only a small fraction of true R&D spending in the economy. Recent studies have expanded the scope of the R&D literature by studying the impact of R&D capital on firm earnings and market value. Lev and Souginannis (1996) report that R&D capital has a positive impact on operating income across a wide variety of industries in the 1975-1991 period. They also document a significant inter-temporal association between R&D capital and subsequent stock prices and returns based on a robust estimation of lagged, panel data. Morbey's (1988) study of R&D spending in major US companies between 1976 and 1985 reports a strong association between R&D and subsequent growth in firm sales. His results also suggest that there exists very little correlation between R&D intensity and profitability. Ettlie's (1998) study of 600 manufacturing firms reports that R&D intensity is significantly associated with improvements in market share after controlling for firm size, industry and geographic region. His study shows that R&D spending is also associated with greater computerization of manufacturing and increased agility as measured by qualitative indicators of manufacturing performance. Lev and Sougiannis (1996) showed that the association between R&D expenditures and subsequent earnings is positive and economically significant. In an empirical study of firm performance across US and Japanese firms, Lee and Shim (2002) observe that the impact of R&D on a firm's long run performance is significant and positive. Hence, there exists a stream of literature which suggests that R&D investments make a positive contribution to firm productivity and profitability growth although most studies have been limited to studying firms in the pre-Internet era, i.e prior to 1995.

More recently, there have been articles presenting a mixed evidence of the benefits of R&D. Chan et al. (2001) explore the relationship between R&D expenditures and the equity market value of firms between 1975 and 1995. Although their study does not support a direct link between R&D spending and future stock returns, their results also suggest that R&D intensity is associated with greater volatility in stock returns after controlling for firm, size, age and industry effects. A recent study by BoozAllen Hamilton of 1000 publicly held, global firms, that spent the most on R&D in 2004, reports that there is no relationship between R&D spending and the several measures of economic success including sales growth, profitability, market value, or total shareholder return. Their study implies that there is a fundamental disconnect between R&D spending and performance where simply throwing greater amounts of money on new product innovation does not guarantee success.

2.2 Impact of IT Spending

The effect of computerization on productivity and firm sales growth has been studied extensively since the late 1980's (Brynjolfsson and Hitt, 1993, 1996a, 1996b; Barua, Kriebel, and Mukhopadhyay, 1991; Dewan and Min, 1997). These studies were able to provide categorical evidence to refute earlier claims related to the "IT productivity paradox" which suggested that the benefits of IT spending were not observable in aggregate output statistics. Brynjolfsson and Hitt's (1996a, 1996b) studies on measurement of IT-driven firm productivity showed that IT spending made a substantial and significant contribution to firm output (i.e sales). Using firm-level data on a panel dataset of large firms from 1987-1991, they observed that the marginal product of computer capital was at least as large as the marginal product for other types of capital investments. Their results suggest that the IT productivity paradox disappeared by 1991, and that firm-level IT spending lead to significant improvements in product quality and variety, which in turn lead to greater firm output. Subsequent work also showed that IT investments are associated with significant returns on spending when they are accompanied by organizational process changes that are associated with improvements in human capital (Hitt and Brynjolfsson, 2000). More recent work show that the contributions of computerization, when accompanied by relatively large investments in complementary inputs such as changes in organizational capital that happen over several years, can be observed only when studies focus on a longer time horizon (Brynjolfsson and Hitt, 2003).

Although prior empirical studies confirm the productivity impact of IT, most studies show either a negative or no effect of IT investments on profitability (Hitt and Brynjolfsson 1996; Rai, Patnayakuni and Patnayakuni 1997; Aral and Weill, 2007). These findings appear to contradict other evidence showing that firms benefit from IT investment, prompting Dedrick, Gurbaxani and Kraemer (2003, p. 23) to call it "the profitability paradox" and others to question the strategic value of IT investments (Carr, 2003; PricewaterhouseCoopers, 2008). Since there have been a significant shift in the nature of IT services in the Internet era, as compared to pre-Internet era on which most earlier studies were based, it is imperative to develop a better understanding of the impact of IT on firm profitability. Newer types of IT systems that form the foundation of web-based computing are expected to have far greater transformational potential compared to their predecessor systems (Dos Santos et al. 1993; Aral and Weill, 2007; McAfee ad Brynjolfsson, 2008).

In this context, the focus of current research has shifted from studying the aggregate impact of IT investments to an evaluation of the role of strategic and informational IT assets and their relationship with firm profitability measures (Aral and Weill, 2007). In other words, we need to understand specific mechanisms through which IT can impact firm performance through improvements in the effectiveness and efficiency of business processes. We argue that one such process that deserves closer investigation is the innovation or R&D process where IT investments have created a significant competitive advantage for firms in many knowledge-intensive industries.

2.3 Role of IT in R&D Processes

Information technology plays a critical role in the success or failure of R&D projects. The knowledge-based view of the firm suggests that innovation processes are critical to generate new knowledge in the execution of R&D projects (Kogut and Zander, 1992; Nonaka and Takeuchi, 1995). In order to leverage the tacit and explicit knowledge that resides within and outside firms' boundaries, firms must build extensive capabilities in identifying and processing the information that resides within the workplace and can frequently involve external partners (Sakakibara, 2001; Cohen and Levinthal, 1990). Research on organizational learning suggests that this knowledge can be captured through technology sourcing routines (Nicholls-Nixon and Woo, 2003) which allow firms to leverage into the knowledge-base of its partner network. IT can help the firms build "high bandwidth" channels with their lead partners and mainstream customers to sense tacit and emerging customer/supplier information (Zeithaml and Bitner, 1996). The consumer packaged goods giant, Proctor and Gamble, has invested heavily in IT-driven innovation solutions as part of new product development efforts (Bloch and Lempres, 2008). For example, until recently, P&G used physical mockups of products on shelves when they engaged consumer focus groups or retailers in the development of new products. With the advent of new virtual reality and simulation tools, P&G now leverages its technology centers to provide three-dimensional views of the storefront which allows customers to provide immediate feedback on product placement and packaging decisions. Implementation of these

IT solutions has reduced the time to create a product mockup from six weeks to a few days, cut costs, and is now used in almost 80% of P&G's R&D initiatives (Bloch and Lempres, 2008).

The examples cited above show how IT can be used to enable R&D processes and improve the execution of R&D projects by increasing the consistency, alignment and relevance of these projects. A review of the prior literature shows that the impact of R&D and IT on firm productivity and profitability has been treated separately in a vast majority of the studies. In other words, most firm-level studies have focused either on the impact of R&D on firm output and profitability, while others have studied the impact of IT on firm outcomes while treating R&D and other discretionary expenditures (such as advertising) as control variables. To the best of our knowledge, few (if any) studies have explored the role of IT in enabling and moderating the impact of R&D investments on firm performance. In other words, most studies on measurement of R&D and IT-driven productivity have focused on the direct impact of R&D or IT or both. However, we believe that while the initial focus on measuring the direct impact of IT in the initial stages of industry-wide computerization was useful, it is even more important to develop a more nuanced understanding of the indirect impact of IT.

An alternate pathway of measuring the impact of IT is to focus on its role as an enabler of knowledge-generating R&D processes. In other words, can smarter use of IT make R&D investments more productive? An important issue in improving R&D productivity is the capability to facilitate seamless communication among virtual product design teams (Nambisan, 2002; Loch and Terwiesch, 1998). New types of information technologies, such as product lifecycle management (PLM) software and advanced supply chain management solutions, enable product design teams to collaborate across inter-organizational boundaries, gather and share design requirements, conduct design iterations, verify and test product designs, and facilitate final design hand-offs to other departments (Adler, 1995; McGrath and Iansiti, 1998). Such web-based tools provide an information rich medium that supports collaboration by facilitating synchronous communication within and across R&D teams (Bardhan 2007). These tools also provide efficient data storage, electronic retrieval and reuse of product designs, and allow R&D teams to compress the overall product development time by reducing latency. Improvements in design quality arise from the ability to share design ideas between team members electronically and conduct real-time version control, which enables engineers to track design defects and implement design changes more efficiently.

These information technologies play a critical role in enhancing the productivity of R&D processes by reducing the overall time to market and product development cost as shown in a recent empirical study by Banker, Bardhan and Asdemir (2006).

In the next section, we use the pharmaceutical industry as an example of an industry sector where new advances in IT have significantly changed the R&D processes involved in drug development. We describe how IT is used to reduce the overall time to market in the clinical trials, a key process within the overall R&D of pharmaceutical firms. Using a grounded case study, based on interviews with managers at an emerging biotechnology firm, we describe the role of IT in managing their drug identification and development processes.

2.4 A Case Study of a Bio-pharmaceutical Firm

We conducted a detailed case study to understand the role information technology plays in the three phases of R&D of new large molecule drugs at Alpha Laboratories, a California-based public bio-pharmaceutical company (company name disguised per their request). Ever since the invention of recombinant insulin in 1982, the application of bio-technology to the creation of large molecule therapeutic drugs ("bio-pharmaceuticals") has grown dramatically. Scientific research and new product development play a central role in the growth of the bio-pharmaceutical industry. Large companies spend more than 20% of revenues on R&D, while smaller companies spend a much larger fraction (100% or more of their sales) to create a robust product pipeline. However, in recent years, the industry has come under increasing scrutiny from both investors and regulators. A host of factors including impending patent expirations, failure of ongoing drugs developed during clinical trials, drug side-effects, informed consumers (patients), and a demanding payee group (made up of both insurance companies and government) as well as looming competition from global rivals have created a difficult financial situation for most companies including Alpha who feel compelled to produce more return on their R&D investments. To improve both the efficiency and effectiveness of their R&D investments, companies such as Alpha have turned to the careful application and assimilation of information technology. We studied how IT has impacted the drug discovery and development processes, with an eye towards both opportunities and challenges.

Due to the large (nearly $1 Billion) investment needed for commercialization, Alpha like other smaller bio-technology companies allied in September 2002 with a larger pharmaceutical company ("Mega") based in the mid-Western United states. This created the need for many years of close interactions between management professionals and at times scientists at both these companies during the three R&D phases: discovery, development, and commercialization. Based on both observations as well as interviews with key development managers, we found that the increasing intensity of the usage of information technology greatly facilitated the collaboration between companies, especially increasing the frequency of communication while reducing the frequency of travel between the locations situated thousands of miles apart.

IT has also helped Alpha simplify, standardize, and streamline its drug discovery and development processes. In the early discovery stages, the company is keeping a close track of all the compounds screened and the results obtained from their tests. While this data used to be recorded in individual scientist notebooks, these are increasingly captured in an enterprise software system available all throughout the company as well as to its development partner. In addition, technology has helped automated a number of enabling steps such as (a) lab supplies procurement, (b) screening of compounds, and (c) synchronization of team members from multiple functional disciplines.

IT has greatly altered the development phase of R&D, which involves multiple rounds of testing to establish the safety and efficacy of the drug developed. This phase starts with pre-clinical tests done both in-vitro and in-vivo, which generate a lot of data. This is followed by clinical tests with humans in increasingly large numbers. As other observers have also noted (Marwaha et al. 2007), IT plays an increasingly critical role in orchestrating the clinical trials processes using systems such as electronic case report forms and electronic data capture formats. While much more remains to be done to reduce the cost and time incurred in conducting clinical trials, efforts are afoot to significantly improve the data quality and efficiency of multiple rounds drug testing. Alpha developers also kept detailed record of their time spent in the project, which is very helpful in coordinating with Mega which underwrites the cost of development.

Alpha launched two drugs to treat metabolic disorders (specifically diabetes) which received approval in the Spring of 2005. The company has since then been busy launching and ramping up the roll out of these approved drugs. The company uses information technology to synchronize both its supply and demand chains. More recently, the company has also started working with drug distributors and retailers to automate the refilling process and ensure prescription compliance. Alpha also diligently collects and analyzed data on side-effects or issues from using these drugs. The data collected from the above three phases is used by Alpha’s senior management to make portfolio investment decisions. In addition, to improve its execution of business processes across the board, the company has put in place a metrics dashboard. Key metrics are collected and regularly tracked. To reduce the burden on collecting and tracking metrics, the company has rolled out software that automatically compute and communicate key metrics from the raw data input by the scientists. These tools have helped the company overcome the initial resistance to implement a metrics-driven management approach from its scientists due to the increased effort required to track these metrics.

Alpha’s scientific and business managers report that IT has greatly helped improve the company’s efficiency, product pipeline visibility, and responsiveness to new market and technical information. A key challenge for the company’s senior management is to broaden its product pipeline to target adjacent market opportunities. IT seems to have helped it initiate many more projects without having to add concomitant resources. There are still some challenges associated with the presence of IT silos across the different phases of R&D; the information generated from the discovery stage is not well integrated with the development stage, which is quite disconnected from the commercialization organization. Also, the discovery processes are still in the rudimentary stages in the application of IT to streamline them. Yet, the company leaders report that they could not have built revenues exceeding $500 million in 3 years without the crucial enabling role of information technology.

Similar observations on the role of IT in pharmaceutical R&D have been made by other researchers and practitioners. Marwaha et al. (2007), in a McKinsey & Company sponsored study, discuss in detail the impact of IT on improving the cost and time incurred in running clinical trials. This study states that IT can help reduce the time required to gather data on clinical trials from twenty to two weeks, on average (Marwaha et al., 2007). Four areas where IT can be a catalyst for improving the productivity of the R&D process are: (a) integrated, enterprise-wide planning of clinical trials to improve resource allocation across clinical teams, (b) providing tools to create electronic case report forms (eCRFs) rapidly by using modular designs and reusable components, (c) enabling physicians and researchers to use electronic data capture (EDC) tools by providing standardized interfaces and ease of use, and (d) developing an integrated IT architecture to eliminate bottlenecks by providing end-to-end visibility across the clinical trials process. Figure 1 provides a useful perspective on the role of IT in clinical trials management. It shows the various trial phases that encompass the design of protocols, creating regulatory documents, to setting up data collection and site selection, to the recruitment of patients and investigators, to the final closeout and reporting phases of the trial. IT plays an important role in several functional areas of the clinical trials process.

One challenge in measuring the value of IT is the fragmented nature of the IT platform and data architecture of most pharmaceutical firms (Marwaha and van Guiken, 2005). Even at Alpha, we found that the discovery, development, and commercialization organizations of the company are under different IT "silos". Implementing an integrated IT platform could off several potential benefits: (a) reduce bottlenecks in the availability of experimental subjects (patients) by providing greater visibility into the patient recruitment pipeline, (b) streamline workflows by providing automated notification, such as alerts in clinical trials management systems to provide warnings when data entry is delayed and/or trigger follow-up actions to reduce bottlenecks, and (c) provide standardized interfaces that can help firms analyze and compile trials data received from a number of different study partners. Such integrated use of information technology and adoption within core business operations such as R&D constitute the next frontier in the assimilation of IT within major companies.

3. 1. Theoretical Model

We now seek to establish a simple theoretical framework for our empirical analysis of the joint impact of IT and R&D on firm performance. Our analysis differs from the previous literature (both theoretical and empirical works) in two major ways. First, our goal is to model the impact of R&D and IT investments on firm performance measures (such as unit gross margin), not just on economical measures such as productivity growth. Secondly, we are interested in how IT interacts with R&D and the overall impact on firm performance.

A firm's financial performance can be measured in several ways, but a key metric closely impacted by &D is the firm's gross margin, which is the difference between sales and cost of goods sold (COGS) expressed as a percentage of firm sales.[2] Unlike most other financial measures, a firm's gross margin is mostly under the control and influence of R&D

[2] Sales & COGS correspond to Compustat line items 12 and 41, respectively.

performance. Prior research on innovation has shown that approximately 70% of the final cost of a product (i.e. the cost reflected in the gross margin) is driven by R&D-based design decisions, such as the degree of standardization and level of product complexity (Jaruzelski et al. 2005). Hence, the gross margin represents an appropriate financial measure of R&D-driven product innovation that culminates in greater sales from new product development.

In this paper, we model that R&D investments will improve a firm's gross margins through the improvement of a product's performance quality (q_t). We use a model similar to that used in the economics literature where a firm's product gross margins (m_t) at time t can be related to product quality (q_t) at time t as shown below.

$$m_t = C + \beta q_t - \varepsilon q_t^{\ 2} \quad (\beta,\, \varepsilon > 0) \tag{1}$$

Here, m_t is the unit gross margin of a single product at time t which is defined as the difference between a product's price (which is a function of quality) and the product-specific costs. Although quality alone has a positive impact on margin, increase in the variable cost negatively impacts the gross margin. The impact of the variable cost is reflected in the variable cost coefficient ε in the above equation. For goods with negligible variable costs, such as for digital products and even pharmaceuticals, ε is close to or equal to zero. On the contrary, for industrial goods, variable costs are substantial and $\varepsilon > 0$.

We model that the firm's product quality is mainly a function of investments in R&D, but also influenced by the interaction between R&D and IT investments, as explained in the previous section. Specifically, this interaction arises due to IT's ability to capture customer needs better and incorporate features that raise customer willingness to pay. In our model; quality (q_t) is related to R&D investment (z_t) and IT investments (I_t) at time t in a simple manner as follows:

$$q_t = q_{t-1} + \alpha z_t + \mu z_t I_t \quad (\alpha,\, \mu > 0) \tag{2}$$

In equation (2), we assume that R&D (respectively IT) investment at time t is independent of the investment of R&D (respectively IT) of the previous time period t-1. The above model which is intentionally very simple leads to a couple of straightforward predictions and a couple of more nuanced observations as discussed below.

Model Prediction 1: *A firm's unit product gross margin (m_t) is monotone increasing in R&D investments (z_t) for products with negligible variable costs (ε = **0**), and conditionally monotone increasing for variable cost intensive products (ε > **0**).*

Proof: Substituting equation (2) in equation (1) we obtain the following form of the unit gross margin (m_t)

$$m_t = C + \beta q_{t-1} + \beta\alpha z_t + \beta\mu z_t I_t - \varepsilon(q_{t-1} + \alpha z_t + \mu z_t I_t)^2 \tag{3}$$

Equation (4) is obtained by expanding the squared term of equation (2).

$$\begin{aligned} m_t = C + \beta q_{t-1} + \beta\alpha z_t + \beta\mu z_t I_t - \varepsilon q_{t-1}^2 - 2\varepsilon\alpha q_{t-1} z_t - 2\varepsilon\mu q_{t-1} z_t I_t \\ - \varepsilon\alpha^2 z_t^2 - \varepsilon\mu^2 z_t^2 I_t^2 - 2\varepsilon\alpha\mu z_t^2 I_t \end{aligned} \tag{4}$$

We assume that m_t is twice differentiable of both variables z_t and I_t, that is, its second derivative exists at each point. The first-order partial derivative of equation (4) with respect to z_t is obtained in equation (5).

$$\frac{\partial m_t}{\partial z_t} = \beta\alpha + \beta\mu I_t - 2\varepsilon\alpha q_{t-1} - 2\varepsilon\mu q_{t-1} I_t - 2\varepsilon\alpha^2 z_t - 2\varepsilon\mu^2 z_t I_t^2 - 4\varepsilon\alpha\mu z_t I_t \tag{5}$$

For products with negligible variable costs ($\varepsilon = 0$), equation (5) becomes

$$\frac{\partial m_t}{\partial z_t} = \beta\alpha + \beta\mu I_t \tag{6}$$

Because the first-order partial derivative of m_t with respect to z_t is positive, we conclude that m_t is monotone increasing in z_t for products with zero variable costs.

When the variable cost, ε, is not negligible, then the second-order partial derivative of m_t with respect to z_t becomes negative for any arbitrarily chosen constant value of I_t as shown in the following equation.

$$\frac{\partial^2 m_t}{\partial z_t^2} = -2\varepsilon\alpha^2 - 2\varepsilon\mu^2 I_t^2 - 4\varepsilon\alpha\mu I_t \tag{7}$$

The positive impact of quality on gross margins (β, the coefficient of q_t in equation 1) is much higher than the negative impact of the increased quality that is reflected through the variable costs (ε) on gross margin. Therefore, we assume that $\beta >> \varepsilon$. Then, the first-order partial derivative of m_t with respect to z_t (as illustrated in equation 5) is initially positive and may become negative depending on the magnitude of z_t and the relative magnitudes of the coefficients of equation (5). The function m_t is monotonically increasing in z_t initially for the positive values of the first-order partial derivative of m_t. Since the second partial is always negative, as the first-order partial becomes negative, the product gross margin m_t starts decreasing in z_t. Therefore, m_t is conditionally monotone increasing in z_t for variable cost intensive products. □

Model Prediction 2: *A firm's unit product gross margin (m_t) is monotone increasing in IT investments (z_t) for products with negligible variable costs (ε = **0**), and conditionally monotone increasing for variable-cost intensive products (ε > **0**).*

Proof: The first-order partial derivative of equation (4) with respect to I_t is obtained in the following equation.

$$\frac{\partial m_t}{\partial I_t} = \beta\mu z_t - 2\varepsilon\mu q_{t-1} z_t - 2\varepsilon\mu^2 z_t^2 I_t - 2\varepsilon\alpha\mu z_t^2 \tag{8}$$

The proof follows from the proof of Prediction 1. For products with negligible variable costs ($\varepsilon = 0$), equation (8) becomes

$$\frac{\partial m_t}{\partial I_t} = \beta\mu z_t \tag{9}$$

Since the first-order partial derivative is always positive, m_t is increasing monotonically in I_t.

When the variable cost, ε, is not negligible, then the second-order partial derivative of m_t with respect to I_t becomes negative for any arbitrarily chosen constant value of z_t as shown in the following equation.

$$\frac{\partial^2 m_t}{\partial I_t^2} = -2\varepsilon\mu^2 z_t^2 \tag{10}$$

Based on the assumption that $\beta >> \varepsilon$, the first –order partial derivative of m_t with respect to I_t is initially positive. As the first-order partial stays positive for increasing I_t, m_t keeps increasing monotonically in I_t. Therefore, the increase in m_t with respect to I_t is conditionally monotone for products with positive variable cost, $\varepsilon > 0$. □

Model Prediction 3: *The interaction effect of R&D and IT investments on firm's unit gross margin is monotone decreasing with both the size of R&D and IT investments; the* *drop in the interaction effect is greater in magnitude with respect to R&D investments than the decrease with respect to IT investments.*

Proof: Let INT_t denote the interaction effect of R&D and IT investments at time period t. Mathematically, the interaction effect of R&D and IT investments is the second partial derivative of m_t with respect to z_t and I_t as expressed below.

$$INT_t = \frac{\partial^2 m_t}{\partial z_t \partial I_t} = \beta\mu - 2\varepsilon\mu q_{t-1} - 4\varepsilon\mu^2 z_t I_t - 4\varepsilon\alpha\mu z_t \quad (11)$$

It is easy to see from equation (11) that INT_t is a decreasing function of both z_t and I_t. Depending on the values of the parameters in equation (11), the interaction effect can be a positive value at time zero and it decreases monotonically as investments in R&D and IT increases in time t. Increasing R&D spending results in greater decreases of the interaction effect of R&D and IT on gross margin relative to the same unit increase in IT spending. □

Prediction 4: *Additional R&D and IT investments yield a higher decrease in interaction effect for firms in industries with higher variable costs (*ε *>* **0***).*

Proof: The proof follows immediately from equation (11). The decrease in the interaction impact is larger for higher values of ε. As the variable cost (i.e., ε) approaches zero, the interaction effect becomes a positive constant.

4. Research Hypotheses

We now translate the above analytical model predictions into testable hypotheses.

While the financial impact of R&D investments can be appropriately measured using gross margin as an indicator, we also seek to measure their impact on the underlying knowledge production function. We study how R&D investment impacts a firm's innovativeness using a firm's Patent count, a key measure of the intellectual contribution of a firm's R&D spending. Patent count (PC), measured as the number of patents generated relative to a firm's sales, is a measure of the productivity of R&D processes (Lanjouw and Schankerman, 2004). Prior research on patent quality and research productivity has used this variable as an indicator of R&D productivity since it represents the inventive output of R&D (Caballero & Jaffe, 1993; Kortum, 1993). Several measures of patent count have been proposed in the literature including the patent/R&D ratio which is measured as the number of patents per R&D dollar (Lanjouw and Schankerman, 2004), number of patent citations by other firms, and royalties or licensing revenue derived from patents. We extend R&D's impact on gross margins to knowledge production as reflected in company patents as well.

Using gross margins and patent count as performance measures, we state four hypotheses inspired by the predictions from our simple model.

Hypothesis 1 (H1): *R&D spending has a positive impact on firm performance.*

H1a. *Greater levels of R&D spending are associated with higher firm financial performance, as measured by firm gross margin.*

H1b. *R&D spending has a positive impact on firm innovation, as measured by firm patent count.*

Prior research on the impact of IT spending on firm performance has provided mixed evidence. Researchers have empirically linked IT investments to improvements in firm labor productivity, total factor productivity, output growth, and Tobin's q using cross-sectional and longitudinal data (Prasad and Harker, 1997; Barua et al. 1995; Brynjolfsson and Hitt, 1996; Brynjolfsson and Hitt, 2003; Bharadwaj et al. 2000; Bresnahan et al., 2002). However, the evidence directly linking IT investments with improvements in firm financial performance is less clear. Based on their analyses of firm panel data from the pre-Internet era, Hitt and Brynjolfsson (1996) and Rai, Patnayakuni and Patnayakuni (1997) reported that IT did not have a significant impact on firm profitability. Recent studies have focused on the pathways through which IT investments can create value, using the resource-based view of the firm as the theoretical framework to study the impact of IT-enabled capabilities on firm performance (Bharadwaj, 2000; Banker et al. 2006; Aral and Weill, 2007; McAfee and Brynjolfsson, 2008). Dedrick et al. (2003, p. 23) coined the term "profitability paradox" to refer to the general failure of studies to show a positive relationship between IT investments and other measures of firm financial performance. Kohli and Devaraj (2003) support this observation and state that the impact of IT investment on measures of profitability is mixed at best.

Is IT alone a sufficient tool in itself to improve the firm performance? Or does it serve as a catalyst to improve the productivity of other business processes? Dos Santos et al. (1993) and, more recently, Aral and Weill (2007) observe that while overall IT spending is not associated with firm market value, transformative IT investments that enable new types of business process capabilities are associated with improvements in firm margins and return on assets. Shah and Shin (2007) observe that IT spending contributes to growth in firm profitability through improvements in their inventory turnover ratio based on a large panel study of firms in the manufacturing sector. In a study of pharmaceutical companies conducted by McKinsey, Marwaha et al. (2007) report that IT is used to streamline clinical trials processes by using electronic data capture tools to reduce the cycle time required for collection and analyses of clinical trial data. A new generation of IT tools are now being used to integrate the planning process for clinical trials through modular, reusable IT components that can improve end-to-end coordination, provide greater transparency and improve resource allocation across trials.

In this study, we seek to investigate how IT impacts the relationship between R&D spending and firm performance. We posit that smart IT investments will help R&D managers improve the productivity of their product innovation processes by providing greater capabilities to harness the knowledge embedded across firm boundaries and enable easier (and faster) access to critical product design data that help to reduce product time to market and overall product development costs. Hence, we hypothesize that,

Hypothesis 2 (H2): *IT spending moderates the relationship between R&D spending and firm performance.*

H2a: *IT spending moderates the impact of R&D on firm profitability, as measured by firm gross margin.*

H2b: *IT spending moderates the impact of R&D on the productivity of firm innovation, as measured by its patent count.*

Figure 2 describes our conceptual research model and our hypotheses in terms of (a) the direct effect of R&D, and (b) moderating role of IT on the relationship between R&D spending and firm performance.

Based on a recent series of empirical studies by Booz Allen Hamilton (Jaruzelski et al. 2005; Kandybin and Kihn, 2004), we note that spending more on R&D may not necessarily improve the impact on firm performance. The results of their study indicate that there is a performance disconnect between R&D spending intensity (measured as % of sales) and most discernible measures of business success such as sales growth, gross profit, operating profit and total shareholder return. They divided their sample based on indexed performance levels into three groups: bottom 10%, middle 80%, and the top 10%. Their analyses show that, although there are substantial differences between the firms in the bottom 10% and other two groups, the differences between the middle 80% and top 10% of firms are negligible in terms of profitability and shareholder returns. Indeed, their results suggest that spending on R&D beyond a certain point results in diminishing marginal returns. Their results imply that, while a base level of R&D investment is necessary, it is the effectiveness of this spending that matters more instead of the magnitude of the investment.

What is the optimal level of R&D spending necessary to keep a company ahead of its competitors? Is there such a convention that identifies how much to spend on R&D for a typical firm? Some firms adjust their R&D spending based on a fixed R&D intensity level, at least, over the short term. Mank and Nystrom (2001) argue that R&D spending plays an important role in the introduction and growth phases of the product lifecycle. However, as the product matures, the marginal returns from increased R&D spending diminish over time. Kandybin and Kihn (2004) propose the concept of an “innovation effectiveness curve” where R&D investments are plotted against their marginal return. Their study suggests that many firms increase their R&D spending without altering their processes, organization structures, or capabilities that determine return on investment. Indeed, their analyses of firms in the consumer healthcare sector shows that the most effective cohort spent 4.8% of sales on R&D while the least effective cohort exhibited an average R&D intensity of 5.9%.[3]

Our observations based on returns to R&D spending are also corroborated by another category of discretionary expenditure, namely IT spending. Based on extensive benchmarking studies on IT spending, Rubin argues that contrary to traditional thinking, higher spending on IT does not necessarily correlate with better business performance (Gruman, 2007). After a certain point, extra spending on IT does not yield greater returns. For example, Gruman (2007) observes that the ceiling point for IT investments among financial institutions in his study sample is about 9.1%, beyond which IT spending reaches a saturation point and results in diminishing returns.[4] The optimal IT spending level (or intensity) varies by industry due to different business models and the degree to which different business functions across different industries. Based on these arguments, we hypothesize that spending on R&D and IT may be subject to diminishing returns to scale.

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[3] Effectiveness was measured as new product profit divided by the R&D spending level.

[4] Rubin tested this optimal IT intensity concept by creating IT intensity charts for more than a dozen industries using their historical IT spending and financial data.

Hypothesis 3a (H3a): *The overall return on R&D spending is greater among firms that are below-median spenders as compared to firms that are above median.*

H3b: *The overall return on IT spending is greater among firms that are below-median spenders as compared to firms that are above median.*

Our interest in knowledge-intensive industries is driven by recent technological changes that have accompanied the growth of science- and technology-based firms globally. These industries spend a significant portion of their revenues on R&D activities that are far greater than other industrial sectors, including services-based industries. For example, the National Science Foundation estimates that average R&D spending in the pharmaceutical industry since 1985 ranges between 8-10% of sales, while average R&D in the high-technology industry is between 6-8% relative to sales. In comparison, average R&D spending in other industries combined is approximately in the 2-4% range. On average, pharma firms invest five times more in R&D, relative to sales, compared to the average US manufacturing firm.

These knowledge-intensive industries are also characterized by high gross margins. While total R&D spending by the drug industry and the federal government has tripled since 1990 (in real terms), the industry has consistently ranked as one of the most profitable in the US (DiMasi et al. 2003). For instance, pharmaceutical firms in the Fortune 500 averaged about 10.3% return on assets (ROA) while the median return in all other industries was about 4.7% in the year 2005. In spite of high R&D spending, costly and lengthy clinical trials have slowed down the time to market for drug development. In fact, annual approvals of the number of new molecular entities (NMEs) approved by the Food and Drug Administration (FDA) has shown no sustained increase or decrease during the past twenty years (FDA Facts, 2006)[5]. Clearly, the number of new drugs introduced each year has not stayed abreast of increased R&D spending in the pharma industry. In fact, a recent study that explores differences in growth of R&D spending concluded that the number of patents per dollar has declined in industries where R&D spending have risen the most (Lanjouw and Schankerman, 2004).

One of the most important challenges that knowledge-intensive firms face is the greater technological complexity of the product development process. It is important to understand the major factors that improve the innovation process in these industries. For example, leading

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[5] An NME is defined as "a medication containing an active substance that has never before been approved for marketing in any form in the U.S." The total number of NMEs approved fell from a high of 53 in 1996 to a low of 17 in 2002 before rebounding to 34 in 2004.

pharmaceutical companies raised the productivity of the clinical trial processes by introducing several IT initiatives. These initiatives provided cross-trial transparency across the organization, enabled physicians to use electronic data capture tools more effectively, and managed workflows to eliminate the bottlenecks. Figure 1 provides holistic perspective on the role of IT in improving the productivity and efficiency of clinical trials by enabling a single, common plan of record, enabling standardized processes, supporting cross-project coordination and improved forecasting to support better resource allocation decisions (Marwaha et al., 2007). Similarly, in other high-tech industries, IT investments play an important role by providing the organizational capabilities necessary to leverage R&D investments into significant reductions in product time to market and product quality which translate into higher gross margins (Banker et al. 2006). Hence, we posit that the moderation effect of IT will make greater impact in knowledge-intensive industries where the rate of technological changes is faster than other, relatively traditional industries.

Hypothesis 4 (H4): *The moderation effect of IT spending on firm performance is higher among firms in knowledge-intensive industries.*

> **H4a:** *The moderation effect of IT spending on firm gross margin is higher among firms in knowledge-intensive industries.*
>
> **H4b:** *The moderation effect of IT spending on firm patent count is higher among firms in knowledge-intensive industries*

4. Research Data

We used data from three different sources in this study. We obtained multi-year, archival data on firm-level IT spending from an international research firm that is well-known for its IT data and research services. The data was obtained under a non-disclosure agreement that protects the confidentiality of the data.[6] The data was collected through an annual survey that is administered to chief information officers (CIOs) and other senior IT executives of large, global firms with the goal of collecting objective metrics on IT investments. This firm collects archival IT investment data, along with other IT investment-related information, as part of its annual, worldwide IT benchmarking survey. IT investments include all hardware, software, personnel, training, disaster recovery, facilities, and other costs associated with supporting the

[6] We will be happy to provide the review team with further details on the identity of the research firm.

IT environment, including the data center, desktop/WAN/LAN server, voice and data network, help desk, application development and maintenance, and outsourcing. In this study, we restrict our locus of interest to the subset of firms for which complete, firm-level IT and R&D spending data are available for the 1998 to 2004 period.

Data on financial and accounting metrics were constructed from the Standard & Poor's database, COMPUSTAT database. We collected firm-level data on gross margins, assets, sales, R&D, and advertising from the Compustat database. We note that the advertising data maintained in Compustat was limited because several firms do not report their advertising expenditures for a few years in our 1998-2004 panel. Hence, we supplemented this data using data obtained from the TNS Media Intelligence (TNSMI) database which collects firm-level advertising data for the period from 2002 onwards. We note that this database provides a more accurate picture of new media advertising that is a fast-growing component of overall advertising expenditures, which includes internet-based advertising as well as traditional advertising spend such as network and cable TV, print media and radio.[7] For those firms for which advertising data was not available, we used the average advertising expenditures (as % of sales) of all firms in that 4-digit NAICS code as a proxy for the advertising intensity. This is a commonly used approach in empirical analyses when some portion of the data for a control variable is missing.

The third source of our data on firm-level patent count was obtained from the US Patent & Trademark Office database. The USPTO publishes annual reports where it provides the patent count and technology class for firms that have at least 40 approved patents per year. For smaller firms in our sample, which did not meet the minimum threshold of 40 patents per year, we used a PERL script to extract the relevant patent count data from the USPTO database.[8]

Our panel data set comprises of eighty firms for which we have complete firm-level data on our main variables of interest, namely gross margins, patent count, R&D spend, IT spend, advertising expenditures, assets, and sales. Overall, we have 560 firm-year observations for 80 firms over 7 years. While we focus mainly on the above data set in our regression models, we

[7] The TNSMI database is a leading source of global, advertising expenditure data for academics and professionals in the area of advertising research and analyses.
[8] For more information on the USPTO patent data, we refer readers to the following web site: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports.htm#by_org. The patent database provides the yearly number of applications and patent grants (i.e. patents approved) for utility, design, plant, and reissue patents granted since 1963.

also collected data on firm-level performance variables for the recent years of 2005 and 2006 and used it in our lagged regression models. The firms in our data set belong to three primary industries: Industrials, Pharmaceuticals, and Computers & Electronics (C&E). The Industrials category is comprised of 44 firms in sectors such as manufacturing, energy, consumer packaged goods, and metals and natural resources. There are 10 firms in the Pharmaceuticals category which consists primarily of drug development firms and medical device makers. The C&E category is comprised of 26 firms that belong to the high-tech computer hardware, software and electronics manufacturing companies. Since R&D spending is a key variable of interest, we dropped service-sector firms which reported little or zero R&D spending.

We selected two variables to measure firm performance: *Gross Margin* (GM) and *Patent Count*. The predictor variables that we use in our econometric models are research and development (RD), information technology (IT), and advertising (ADV) expenditures. Furthermore, we control for firm size using firm assets as a control variable. We also introduce dummy variables to control for time trends by using year dummies for our panel data.[9] *RD*, the research and development expense corresponds to the COMPUSTAT item 46. IT spending is defined as the dollar value of capital and operational expenses to support the IT environment. Consistent with the prior literature on IT and R&D productivity, we define R&D- and IT-intensity as the ratio of firm R&D and IT spending relative to sales, respectively. The ratio of assets to sales (*Assets*) is used as a proxy for firm size.

Table 1 provides the descriptive statistics of our data set. During the time period 1998 to 2006, the average R&D/sales ratio was 5.8% while IT spending and advertising intensity ratios were 3.7% and 2.8%, respectively. The averages gross margin was 40%, while average annual sales for firms in our sample were $18.77 billion. The average number of patents approved per year between 1998 and 2006 was 114. We note that average R&D spending among industrial firms is only 2.4%, while it is approximately five times greater at 13.5% for pharmaceutical firms, and almost four times higher at 8.6% for firms in the C&E sector. However, average IT spending seems to be fairly uniform across firms in the three industry categories varying between a low 3.4% among industrials to a high of 4.1% among C&E firms. While advertising expenditures were roughly similar across Industrial and C&E firms, at 2.8% and 2.1%, respectively, they were marginally higher for Pharmaceutical companies at 4.6% of

[9] For our econometric analyses, we used six year dummies for the analyses of 1998-2004 data.

sales. Figure 3 provides a snapshot of the trends in firm-level IT and R&D spending as well as profitability (measured as gross margin) between 1998 and 2004.

We report the Pearson correlation matrix in Table 2. The correlation coefficients indicate that R&D is positively correlated with gross margin (α=0.689; p<0.001) and patent count (α=0.276; p<0.001). We note that R&D and IT spending are not significantly correlated.

5. Econometric Estimation

In the next sub-section, we focus on the relationship between R&D, IT spending and financial performance as measured through their impact on gross margins. We will subsequently study their impact on innovation productivity, measured by patent count.

5.1 Financial Performance

First, we estimate the effects of the primary variables of interest, R&D and IT spending, through the *main effects model* which is expressed as follows.

$$GM_{i,t} = \alpha_0 + \alpha_1 RD_{i,t} + \alpha_2 IT_{i,t} + \alpha_3 ASSETS_{i,t} + \alpha_4 ADV_{i,t} + \alpha_{5,k} Year_k + \varepsilon_{i,t} \tag{1}$$

The index i represents the firm, while index t represents the year, and the variable $\varepsilon_{i,t}$ denotes the error term. The variables $RD_{i,t}$, $IT_{i,t}$, $ADV_{i,t}$, *and* $Assets_{i,t}$ represent R&D spending, IT spending, Advertising expenditures, and firms assets, respectively, where each variable is scaled by the level of firm *i*'s sales in year *t*. $GM_{i,t}$ represents the gross margin of firm i in year t. $Year_k$ represents a time dummy for each year in our sample.

Next, we estimate the interaction effects of the predictors $RD_{i,t}$ and $IT_{i,t}$ on gross margin. The *interaction effects* model, takes the following form with the addition of the cross-product of the variables *RD* and *IT*.

$$GM_{i,t} = \alpha_0 + \alpha_1 RD_{i,t} + \alpha_2 IT_{i,t} + \alpha_3 ASSETS_{i,t} + \alpha_4 RD_{i,t} x IT_{i,t} + \alpha_5 ADV_{i,t} + \alpha_{6,k} Year_k + \varepsilon_{i,t} \tag{2}$$

We estimate models (1) and (2) using pooled ordinary least squares (OLS) regression analysis. The results of pooled OLS regressions on the *main* and *interaction* effects models are reported in Tables 3 and 4, respectively. We report the standardized regression coefficient estimates and use *Huber White* standard errors to correct for heteroscedasticity when we report the statistical significance of our regression estimates. [10]

We note that we ran the models specified in equations (1) and (2) using the current year values of the independent variables, as well as lagged values for 1-yr, 2-yr, and 3-yr lags of the key explanatory variables: *R&D* and *IT*, and *Advertising*. For explanatory purposes, we will present the results that we obtained using 2-yr and 3-yr lags in this paper. We observe, however, that these results are consistent when we use current year and 1-year lagged values of the independent variables in models (1) and (2). We also note that, although IT spending data was available only from 1998-2004, we were also able to use the 2005 and 2006 data on gross margins when we incorporate 2-yr and 3-yr lags on the independent variables. In other words, the 2-year lagged models using 2006 data on gross margins deploy the 2004 data on R&D, IT, and ADV. We use current year values of ASSETS in the lagged models since the relationship between firm assets and financial performance does not involve a lagged impact.

We present our results for each of the three major industry categories separately. All regressions are statistically significant and explain a significant portion of the variance in gross margins. Estimation results of main effects models, as shown in the first column for each industry, indicate that R&D has a positive and significant impact on gross margin in both 2- and 3-yr lagged models across all industries. We observe that 2-yr lagged IT spending has a marginal, significant impact for pharmaceutical firms, while it is not significant for other industries. The results also indicate that lagged, advertising expenditures have a positive impact on gross margins across all industries. Furthermore, firm size, as measured by Assets, has a positive association with gross margin for firms in knowledge-intensive industries such as pharmaceuticals and C&E. However, assets are negatively associated with profitability among industrial firms, which indicates that larger, industrial firms may be less likely to leverage their size to improve gross margins.

The parameter estimates of the interaction effects model are shown in the second column for each industry in Table 3. These results are qualitatively similar to the earlier results of the main effects models. While the impact of *R&D* is positive, IT has a positive, significant impact on gross margins only in the 3-year lagged models for the Pharma and C&E firms. We

[10] The standardized coefficient is obtained by multiplying the unstandardized coefficient with the ratio of the standard deviation of the regressor to the standard deviation of the regressand.

note, however, that the interaction effect R&D x IT is either negative or not significant in all models. Hence, we find support for hypothesis H1a but not H2a. In other words, while we find support for the main effect of R&D on firm profitability, our preliminary analyses does not support the interaction effect of R&D and IT in terms of its significance on profitability.

It turns out that by simply adding the cross-product terms to the main effects model does not reveal the real impact of the interaction of the key explanatory variables, *R&D* and *IT* on firm financial performance. A better way of investigating the interaction impact is explained in the next section.

5.1.1 Clustering Firms into Quadrants

In our hypotheses development section, we argued that there is some evidence of diminishing returns “beyond a saturation point” when we study the effect of IT and R&D investments on firm profitability. Rubin notes that “… beyond a certain point, extra IT spending does no good…” He refers to this sweet spot as the “optimal IT intensity” (Gruman, 2007). The Booz Allen study makes a similar observation with respect to diminishing returns from R&D spending which Kandybin and Kihn (2004) refer to as “innovation effectiveness” curves. A similar pattern exists in our sample data as evidenced by the plot shown in Figure 4. We plot combined R&D and IT spending against gross margins for C&E firms for the seven-year period of our study. We observe that there appears to be a peak saturation point when combined R&D and IT spending is approximately 20% of sales. Beyond this level, gross margins decline rapidly.

To study this effect carefully, we split the sample data into quadrants based on the values of IT and R&D spending. We use the median values of R&D and IT spending to split the sample into four quadrants as shown in Figure 5. Here, Q1 represents firms in the first quadrant for which R&D and IT spending are less than their corresponding industry median levels in time t, i.e., $R\&D_{i,t} < R\&D_{Med(t)}$ and $IT_{i,t} < IT_{Med(t)}$, respectively. Similarly, Q2 represents firms in the second quadrant where $R\&D_{i,t} > R\&D_{Med(t)}$ and $IT_{i,t} < IT_{Med(t)}$. Q3 and Q4 represent firms in the third and fourth quadrant, respectively.

We run the interaction effects model for firms in each quadrant by introducing a dummy variable, D. In other words, $D_{i,j,t} = 1$ if firm *i* belongs to quadrant *j* in year *t*, and zero otherwise. The model is specified as:

$$GM_{i,t} = \alpha_0 + \alpha_1 RD_{i,t} + \alpha_2 IT_{i,t} + \alpha_3 D_{i,j,t} + \alpha_4 ASSETS_{i,t} + \alpha_5 ADV_{i,t} + \alpha_6 RD_{i,t} xIT_{i,t} xD_{i,j,t} + \alpha_{7,k} Year + \varepsilon_{i,t} \quad (3)$$

We estimate model (3) separately for each industry and quadrant. For example, the dummy variable D_{ijt} =1 for industrial firms that fall in Q1 in year t, and zero for other industrials in quadrants Q2, Q3, and Q4. We observe that the interaction term "R&D x IT" represents the joint impact of R&D and IT. Similar to our earlier estimation, we report the parameter estimates for 2-year and 3-year lags on the independent variables. Using the time-lagged models also allows us circumvent the endogeneity issue which arises when the independent and dependent variables are measured in the same time period which might lead one to question the direction of causality in our models.

We report the parameter estimates for each quadrant and industry category in Table 4, which is partitioned into three panels, each representing a different industry sector. The columns, labeled Q1, Q2, Q3 and Q4, provide parameter estimates for firms in quadrants Q1 through Q4 as shown in Figure 5. Our results indicate that the main effects of R&D, IT and ADV are generally similar to the earlier results described in Tables 2 and 3. However, there are significant differences in the coefficient estimates of the "R&D x IT" interaction term across all industries. Focusing first on industrial firms, we observe that the 2-year lagged estimate of the interaction term is significant for firms in Q1 (coeff.=0.235, $p < 0.001$). Similarly, the 3-yr lagged estimate of the interaction term is significant for Q1 firms (coeff.=0.201, $p < 0.001$). However, the interaction term is not significant for industrials in other quadrants. In other words, firms that spend less on R&D and IT (i.e. firms in Q1) relative to the median industry investment do better than other firms.

This pattern repeats itself for firms in other industries: Pharmaceuticals and C&E. The coefficient estimates of the interaction in the 2-year lagged models are equal to 0.521 and 0.349 ($p < 0.001$) for Pharma firms in quadrants Q1 and Q4, respectively. These results are consistent with the 3-year lagged models where the coefficient estimates are 0.363 and 0.497 for Q1 and Q4, respectively. We now turn our attention to estimates of the interaction term for firms in quadrants Q2 and Q3. We note that these coefficients are either negative or insignificant for both 2-yr and 3-yr lagged estimation models.

The results are similar for C&E firms where our estimation results indicate that the interaction term is positive and significant in Q1 and Q4.[11] Our results suggest that high R&D spenders do not necessarily reap the most returns on their investment. Firms that spend less on R&D compared to their industry peers realize greater benefits relative to their investments. Our results suggest that firms in Q4, which spend less on R&D but more on IT compared to their industry peers, realize greater returns on their investments when compared to firms in Q2 and Q3 that make relatively larger investments in R&D and IT.

To summarize, the interaction effect between R&D and IT is positive when a firm's R&D (or IT) spending is low with respect to the median R&D (or IT) spending of other firms in its industry. That is, firms in quadrants Q1 or Q4 are more likely to realize the positive interaction effect of R&D and IT spending when compared to high-spenders in quadrants Q2 or Q3. When firms spend beyond the point of diminishing returns, the interaction impact between IT and R&D is negative and any incremental spending results in a negative or insignificant impact on firm profitability. Hence, we argue that support for hypothesis H2a is more *nuanced*, i.e. the moderation impact of IT is observed only among firms that are below the median R&D spending level relative to their industry.

5.2 Overall Effect of R&D and IT on Firm Profitability

We now report the overall impact of R&D and IT spending on gross margins in Table 5. The overall impact of R&D consists of two components: (a) *direct* impact which is measured as the regression coefficient of the R&D variable, and (b) an *indirect* component which is measured through its interaction with IT spending. When $D_{i,j,t}$ equals 1 (i.e if firm i belongs to quadrant j in time t), the overall impact of *R&D* can be measured as "$\alpha_1 + \alpha_5 * IT_{avg}$" using the average value of *IT* spending of all firms in quadrant j. Similarly, the overall impact of *IT* on firm performance equals "$\alpha_2 + \alpha_5 * RD_{avg}$" using the average value of R&D. The significance of the overall effect of *R&D* is measured using the t-statistic which is calculated as $(\alpha_1 + \alpha_5 * IT_{avg}) / \hat{\sigma}_{\alpha_1+\alpha_5*IT_{avg}}$. Similarly, the t-statistic for calculating the overall impact of IT spending is calculated as $(\alpha_2 + \alpha_5 * RD_{avg}) / \hat{\sigma}_{\alpha_2+\alpha_5*RD_{avg}}$. Using the average *R&D* and *IT*

[11] The estimates of the interaction term are significant and equal to 0.200 and 0.122 for Q1 and Q4 firms, respectively for the 2-yr lagged models, and 0.178 and 0.113, respectively, for the 3-yr lagged models.

spending values, we calculate the overall impact of R&D and IT spending on firm gross margins and report these values in Table 5 for the 2- and 3-year lagged models.[12]

Our results indicate that the overall impact of R&D and IT spending is positive for firms in Q1 across all industries. Furthermore, their impact is also positive for Pharma and C&E firms in Q4. These results are consistent for all lagged models and reinforce our earlier findings related to the greater overall returns on R&D and IT spending for below-median spenders when compared to high spenders in quadrants Q2 and Q3. We note that while the overall impact of R&D on gross margin is positive for C&E firms in quadrants Q2 and Q3, the magnitude of this impact is small when compared to the effect in Q1 and Q4. Hence, our results support hypotheses H3a and H3b with respect to the overall impact of R&D and IT being greater for firms that are below-median spenders relative to firms that spend more than industry median levels.

We also report the Wald statistics for testing differences in overall impact of R&D and IT spending on gross margins. The Wald test statistics (calculated for each pair of R&D and IT coefficients) are reported on the second row in Table 5 (i.e. row below the coefficient estimate) and shown in italics. Our results suggest that R&D spending dominates the impact of IT spending as evident by the positive and significant Wald statistics.

Next, we calculate the *elasticity* of R&D and IT spending to compare their relative importance in terms of their impact on gross margins. The elasticity of *R&D* is denoted as $e_{R\&D}$, and is calculated as,

$$e_{RD} = \alpha_{RD} \frac{RD_{avg}}{GM_{avg}} \tag{4}$$

where α_{RD} represents the overall parameter estimate for *R&D*. R&D and IT elasticity for the 2- and 3-yr lagged models are shown in Table 6. The results indicate that the elasticity of R&D and IT spending for firms in Q1 dominates their corresponding values for firms in other quadrants. For the 2-year lagged model, the elasticity of R&D spending for Q1 firms in the

[12] We use unstandardized parameter estimates in our calculation of the overall effects of R&D and IT. For instance, using the average R&D and IT spending values of 9.33% and 3.14%, respectively, for pharmaceutical firms in Q1, we calculate the overall effect of R&D on gross margin as equal to 2.16. In other words, a 1% increase in *R&D* results in a 2.16% increase in gross margin for pharmaceutical firms in the first quadrant, assuming an average IT intensity of 3.14%. Similarly, we observe that a 1% increase in IT spending results in a 3.99% increase in gross margin assuming an average R&D intensity level of 9.33%.

C&E industry is 0.422, while the elasticity of IT spending is 0.230. In other words, a 1% increase in R&D results in a 0.422% increase, whereas a 1% increase in IT spending is associated with 0.23% increase in gross margins. In comparison, the elasticity of R&D and IT spending is equal to 0.390 and 0.216, respectively, for Q4 firms and it is significantly lower among high-spending firms in quadrants Q2 and Q3. In general, our R&D elasticity estimates are similar in magnitude to the estimates reported by Griliches and Mairesse (1990) which range from 0.20 to 0.41 for US Manufacturing firms and between 0.20 and 0.56 for Japanese manufacturing firms.

The overall results from Table 6 suggest that the impact of R&D is greater than the impact of IT for all firms irrespective of the quadrant. For the firms in quadrants Q2 and Q3, the elasticity of IT is either very small or negative which is consistent with the results of Table 5. Therefore, when R&D intensity is high relative to the industry median, any increase in IT spending results in an overall decrease in gross margin. We also observe that the elasticity of R&D and IT is significantly greater among firms in knowledge-intensive industries, such as Pharma and C&E, relative to their corresponding values for industrial firms. Hence, our results support hypothesis H4a with respect to the moderation impact of IT being greater within knowledge-intensive industries versus industrial firms.

5.3 Impact of R&D and IT on Patent Count

Our analyses of the impact of R&D and IT follow a similar pattern to our prior analyses using gross margins as the dependent variable. First, we estimate the effects of the primary variables of interest, R&D and IT, through the *main effects model*.

$$PC_{i,t} = \alpha_0 + \alpha_1 RD_{i,t} + \alpha_2 IT_{i,t} + \alpha_3 ASSETS_{i,t} + \alpha_{4,k} Year_k + \varepsilon_{i,t} \qquad (5)$$

$PC_{i,t}$ represents the patent count of firm i in year t, while other model variables are the same as before. We drop $ADV_{i,t}$ from our model specification since the prior literature shows that advertising expenditures are unrelated to patent count. Next, we estimate the interaction effects of the predictors $RD_{i,t}$ and $IT_{i,t}$ on patent count. The *interaction effects* model, takes the following form.

$$PC_{i,t} = \alpha_0 + \alpha_1 RD_{i,t} + \alpha_2 IT_{i,t} + \alpha_3 ASSETS_{i,t} + \alpha_4 RD_{i,t} x IT_{i,t} + \alpha_{5,k} Year_k + \varepsilon_{i,t} \qquad (6)$$

We estimate models (5) and (6) using OLS regressions based on the pooled data over the period 1998 to 2006. We use *Huber White* standard errors to correct for heteroscedasticity and report the standardized estimates in Table 7. To be consistent with our earlier models, we present the results obtained using 2-yr and 3-yr lags while observing that the results are consistent for other lag specifications as well. We note that our analyses focuses on two sectors, namely Industrials and C&E firms, since we do not have enough patent data on pharmaceutical firms for rigorous empirical analyses.

The results of the *main effects* models shown in Table 7 indicate that R&D investments have a positive and significant, lagged impact on the level of intellectual property innovation, measured as patent count. The impact of IT on patent count is either negative or not statistically significant. For the interaction effects models, we observe that R&D has a positive impact only among industrial firms for the 2- and 3-yr lagged models (coeff. = 0.272 and 0.299, $p < 0.001$ in both cases). For C&E firms, we note that the impact of R&D, while positive, is not statistically significant when interaction effects are included. As in the case of gross margins, our results indicate that the interaction effects are not significant in all cases.

We now split our firm sample data into quadrants using the approach described in Figure 5. We run the interaction effects model for firms in each quadrant using the following model specification.

$$PC_{i,t} = \alpha_0 + \alpha_1 RD_{i,t} + \alpha_2 IT_{i,t} + \alpha_3 D_{i,j,t} + \alpha_4 ASSETS_{i,t} + \alpha_5 RD_{i,t} xIT_{i,t} xD_{i,j,t} + \alpha_{6,k} Year + \varepsilon_{i,t} \quad (7)$$

We estimate model (7) separately for Industrial and C&E firms in each quadrant. Table 8 presents our estimation results for the two industry categories for the 2- and 3-yr lagged models. We observe that R&D has a positive and significant association with patent count in both lagged models, while the impact of IT is either negative or not significant. The estimate of the interaction term, R&D x IT, is positive for Industrials in Q4 while it is not significant in other quadrants. However, for C&E firms, the coefficient estimates of the interaction term in the 2-year lag models are equal to 0.146 and 0.101 ($p < 0.001$) in quadrants Q1 and Q4, respectively. These results are consistent with the 3-year lagged estimation models where the coefficient estimates are 0.139 and 0.080 for Q1 and Q4 firms, respectively. For firms in quadrants Q2 and Q3, the coefficients of the interaction term are either negative or statistically insignificant for both lagged specifications.

Our results suggest that high R&D and IT spenders do not necessarily reap the most returns on their innovation investment. Firms that spend less on R&D compared to their industry peers exhibit a higher patent productivity as a percentage of sales. Our results suggest that firms in Q4, which spend less on R&D but more on IT compared to their industry peers, also realize significant returns on their investments when compared to firms in Q2 and Q3 that spend relatively larger sums on R&D and IT.

Analyses of the overall impact of R&D and IT spending on patent development indicate that R&D spending does matter. R&D spending has a significant, positive effect on patent count for both Industrials and C&E firms. Furthermore, this effect is observed across *all* quadrants based on the level of R&D spending relative to the industry median. The results also suggest that the overall impact of IT spending on patent count is positive only for C&E firms and is observed only in quadrants *Q1* and *Q4*. In other words, IT spending has a net beneficial impact on patent innovation in the C&E industry but only among those firms whose relative levels of R&D spending are below that of their industry peers. These results are consistent across different lag specifications and are similar in terms of their significance to the gross margin results reported before.

We also report Wald statistics in Table 9 (in italics) which compare the differences in the overall effect of R&D and IT spending on patent count. These results indicate that R&D spending dominates the overall impact of IT spending among firms across all quadrants. This relationship is not surprising since R&D is the primary driver of innovation among firms and our results empirically show that R&D activity does lead to greater intellectual property creation in two different industries.

Finally, we report the elasticity associated with R&D and IT spending, in terms of their impact on patent count, in Table 10. We note that the average elasticity of 2-year lagged R&D spending among industrial firms (across all quadrants) is 0.744, which means that every 1% increase in R&D sending is associated with a 0.744% increase in patent count (expressed as ratio of sales). Among C&E firms, the average R&D elasticity is 1.23 which suggests that the expected gains in terms of patent creation in the high-tech industry are higher (on average) than the actual cost of R&D. We observe that IT elasticity is positive and significant only in Q1 and Q4, while it is not significant in Q2 and Q3, for both Industrials and C&E firms. On average, the elasticity of 2-year lagged spending for industrial firms is equal to 0.20 in Q1 and

Q4, while it is equal to 0.483 for firms in the high-tech sector. These results are qualitatively similar to the IT and R&D elasticity values obtained using 3-yr lagged models.

5.4 Random-effects Models

In this paper, we focus on the regression models that are estimated through pooled OLS. The pooled regression models might be subject to the *omitted* (or *unobserved*) variable problem since the differences in time are ignored for the cross-section of the firms. The unobserved factors that affect the response variable can be of two types: constant or varying over the time. We treat the unobserved factors that affect the response variable as time-varying, and therefore use the random-effects model in our time-series cross-sectional analyses. Assuming that the unobserved variables are uncorrelated with the regressors, and taking into account the fact that there is little variation within the cross-sections, the random effects model appears to be a better choice over the fixed effects model.

We explore the use of *random-effects* models in a majority of the cases (different combinations of industries and lagged variables) by testing the time-series model with the Hausman specification test. In these models, the null hypothesis cannot be rejected which implies that the choice of random effects models is the correct one. Following prior literature, we chose 2- and 3-year lagged values as representatives of R&D and IT in our random-effects models. We ran the regression models specified in (1) and (2) for each quadrant. The coefficient estimates of the random effects models are qualitatively similar to those of the pooled OLS estimation models that we have discussed in the previous section.

6. Discussion

We now discuss the key implications of our research and summarize our contributions.

6.1 Implications

The above results have several significant implications for researchers and practitioners. Our analyses indicate that profitable innovation cannot be bought simply by throwing money on R&D projects. Based on the findings from our study, we observe that R&D and IT spending are subject to diminishing marginal returns beyond a certain inflection point. Spending above this level result in lower returns since a firm will invest in high value projects first, followed by the next in line based on a rank-ordered scheme, until it is spending money on dubious projects. Both IT and R&D investments must be well coordinated and are most effective for firms that adopt a "lean approach". Our findings are consistent with the results reported by

Kandybin and Kihn (2004) who conclude that "… the solution to innovation anemia is not to boost incremental spending, but to raise the effectiveness of base spending…"

Our results are consistent with an earlier benchmarking study by Booz Allen which reported that the effectiveness of innovation does not correlate well with firm size or the magnitude of the R&D investment (Kandybin and Kihn, 2004). For example, they report that Apple Inc. had an R&D spending intensity of 5.9% that was significantly lower than the C&E industry average of 7.6% in 2004. Yet, Apple's sales growth and profitability was greater than its peers and was primarily-driven by a "portfolio-driven approach" to R&D investments that empowered senior managers to improve the effectiveness of innovation processes by focusing on capabilities, not spending. The findings of our study imply that the IT can play a critical role in improving the effectiveness and efficiency of R&D processes by reducing coordination costs, increasing transparency, making better resource allocation decisions, and improving the overall business value of R&D.

From a managerial perspective, an important implication of our study is to focus on the role of IT in improving innovation capabilities in their R&D organizations. Opportunities to use IT in all phases of the product innovation lifecycle should be explored. For instance, IT systems should be deployed to identify and sense emerging customer needs which will feed the product ideation phase. IT can be used to improve project governance through creation of appropriate project management software and disciplined stage-gate processes that streamline project workflows. From a research dimension, our study provides a fresh perspective into the drivers of firm financial and innovation performance and provides a new causal path that explains how IT can moderate the impact of R&D on innovation and profitability. It addresses a gap in the literature which has heretofore ignored the possibility of interaction effects when studying the relative productivity impact of IT and R&D on firm performance.

6.2. Conclusions

Given that innovation has been a fundamental source of technological change and productivity growth during the last two decades, there is no doubt that R&D is a key driver of such productivity improvements in the economy. In this study, we focus on the role of IT-enabled innovation and the importance of IT investments in moderating the productivity impact of R&D spending. Considering that quantum strides in computing have been made during the IT revolution since the early 1990s, it is important to (a) understand the specific role of IT in improving the innovation capabilities of R&D processes, and (b) measure the impact of R&D and IT investments on firm profitability and patent innovation. While the literature has mostly focused on the impact of R&D or IT spending separately, our study focuses on the critical question: "Does IT spending enhance the productivity and innovation of R&D processes?"

We propose and empirically test our research model using a relatively recent data set that reflects the significant technological changes in knowledge-based industries since the first wave of Internet-based, commercial technologies in the late 1990s. Our study shows that R&D has a significant, positive impact on two metrics that represent the financial and innovation dimensions of firm performance: *gross margin* and *patent count*. Our results indicate that IT spending moderates the impact of R&D spending on firm performance. However, these effects are not observed across the board for all firms. Rather, the moderation impact of IT is observed only for firms that spend below their respective industry median levels, while there are no significant effects for firms that are high spenders of R&D and IT. In other words, there are diminishing returns to IT spending beyond a certain level of saturation. Our results also indicate that the overall impact of R&D and IT spending is greater among firms in knowledge-intensive industries such as Pharmaceuticals and high technology.

Our study has several limitations. First, due to the secondary nature of the data, we do not have insight into the specific types of IT investments that firms in our sample have made during the time horizon in our study. Future research should focus on the types of IT investments made including the allocation between various components of IT spending such as software applications, consulting, and infrastructure investments. Second, the product development time to market in some industries, such as pharmaceuticals, can be in the range of eight to ten years for certain classes of drugs. It is possible that the time period of our study did not allow us to observe the full effects of R&D and IT spending in the Pharma industry. Third, our study uses data on large, global firms. This limits generalization of our findings to similar firms, and further exploration with data from smaller firms is needed.

In this study, our focus was primarily on the accounting and innovation measures that represent firm performance. Future research can extend this line of research to include firm efficiency measures using non-parametric estimation methods, such as data envelopment analyses (DEA) to study the impact of R&D and IT on firm efficiency. Another avenue for potential research includes studying the impact of R&D and IT on financial metrics such as stock returns and firm risk. While R&D investments are considered to be risky, since many R&D projects fail, smart IT investments may serve to lower the volatility of these risks by providing greater transparency into execution of R&D projects, and improving the coordination across multiple projects. New methodologies to estimate the impact of IT on these risks will need to be developed. Finally, additional grounded case studies across different industries are needed to fully understand the process-level impact of R&D and IT investments on organizational innovation capabilities.

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APPENDIX

A.1 Example Illustrating Predictions 1 and 2

<u>*EXAMPLE 1*</u>: Let the parameters C, β, and ε of equation (1) are 3, 0.5, and 0.01, respectively. The coefficient of z_t (i.e. α) is taken to be 0.4 while the coefficient of the interaction term, μ is assumed to be 0.1. The initial value is chosen as 0 for quality (q_t).

We plot the unit product margin m_t with respect to z_t in Figure 1. Note that I_t is assumed to be equal to a constant (here chosen as $I_t = 1$) for all values of t. Similarly, the plot of m_t with respect to I_t is drawn in Figure 2 by keeping z_t constant (in this case it is chosen as $z_t = 3$) for all t.

In both figures, we observe that for positive values of ε, m_t is conditionally monotonically increasing in z_t (or I_t). As the first-order partial becomes negative, m_t starts decreasing in z_t (or I_t).

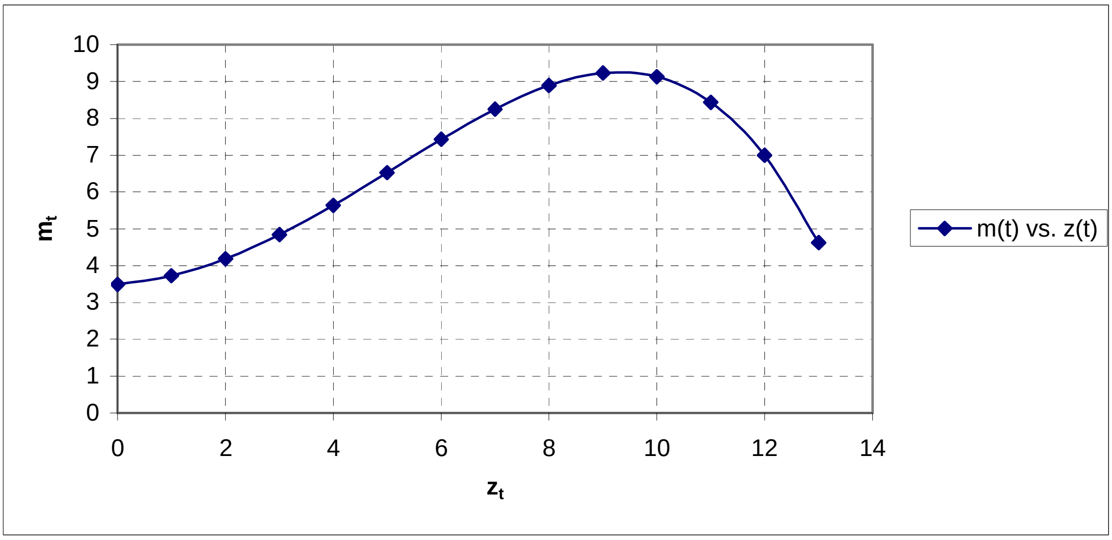

Figure 1: Firm's unit product gross margin (m_t) versus R&D investments (z_t)

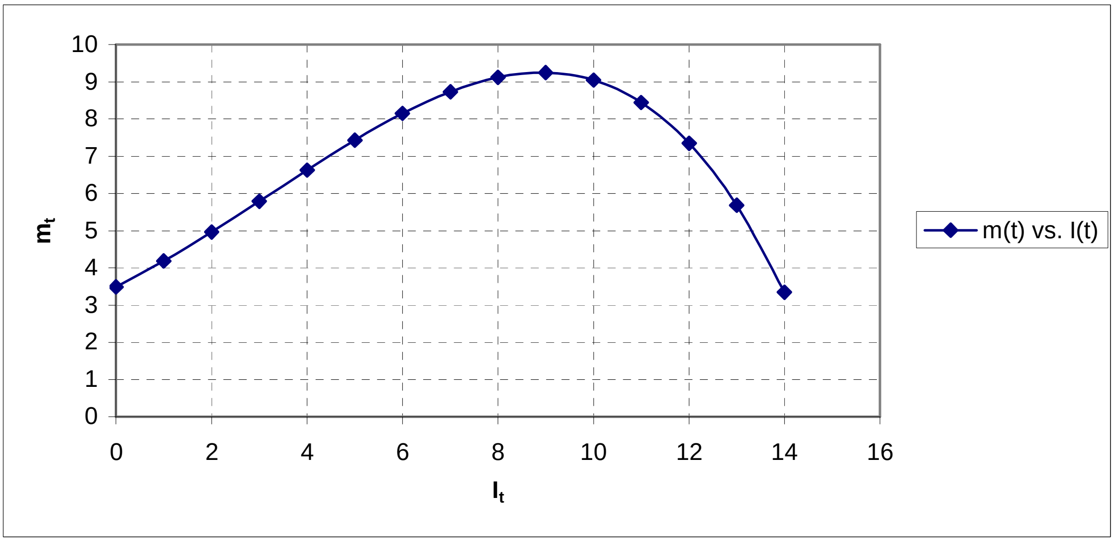

Figure 2: Firm's unit product gross margin (m_t) versus IT investments (I_t)

A.2 Figures and Tables

Figure 3. The Role of Information Technology in Clinical Trials

	Design, Planning	Start -Up	Managing Trial	Closeout	Report
Key activities benefiting from IT	•Designing protocols •Creating regulatory documents •Planning, ordering drugs	•Distributing drugs, information •Setting up data collection •Selecting site	•Monitoring progress, adverse events •Tracking patient enrollment •Tracking clinical-response forms	•Entering, verifying data •Processing clinical-resource forms •Reconciling investigator's queries	• Reporting Outcomes
IT Focus					
1. Clinical Data Management	•Database of investigators to support design of electronic forms	•Standard interface to integrate third-party systems	• Greater computing horsepower allows scientists to design large randomized trials	•Automated data checks to minimize queries	
2. Patient Safety	← Real-time monitoring →				
3. Document Management	← Single data repository with version control, workflow management →				
4. Clinical Trials Management	•Modular design, construction of consent and case report forms	•System to convert study designs to electronic forms and database with minimal rework	•Electronic invoicing •Automated drug supply work flow •Patient mgmt.	•More effective trials managed thru large-scale databases and simulation software	•Report builder
5. Project Management	•Standard data models to work with vendors				

Source. Marwaha, Patil & Singh, McKinsey Quarterly, 2007.

Figure 4. Conceptual Research Model

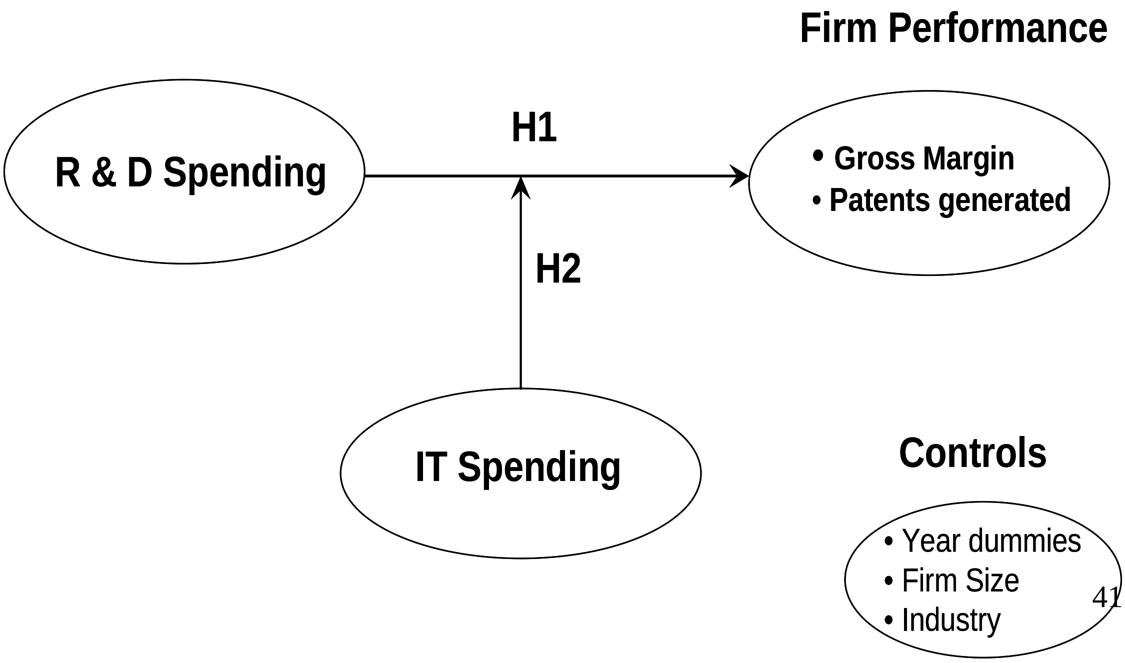

Figure 5. Industry Trends in IT and R&D Spending and Firm Profitability: 1998-2004

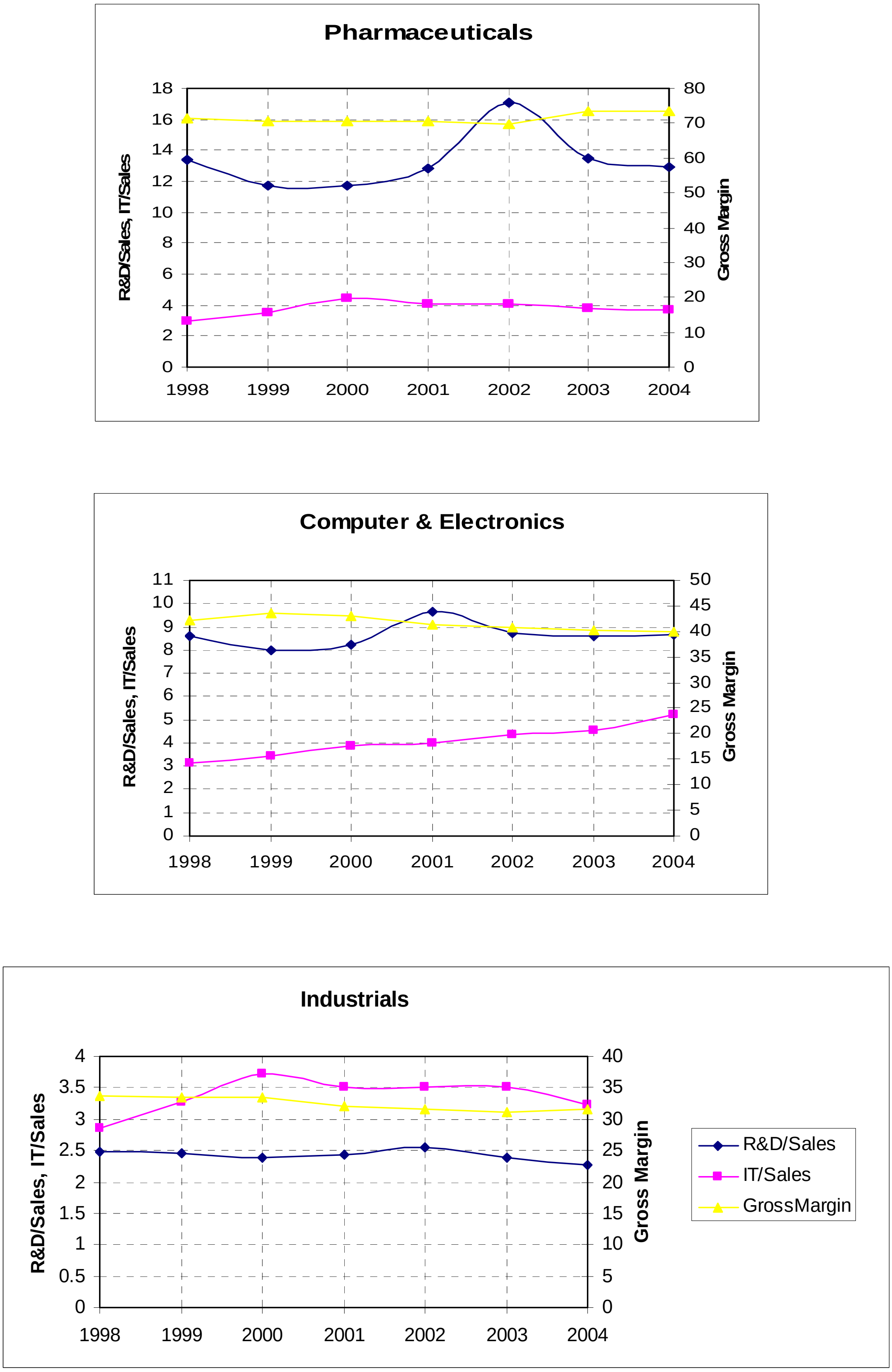

Figure 6. Diminishing Returns to IT and R&D Spending

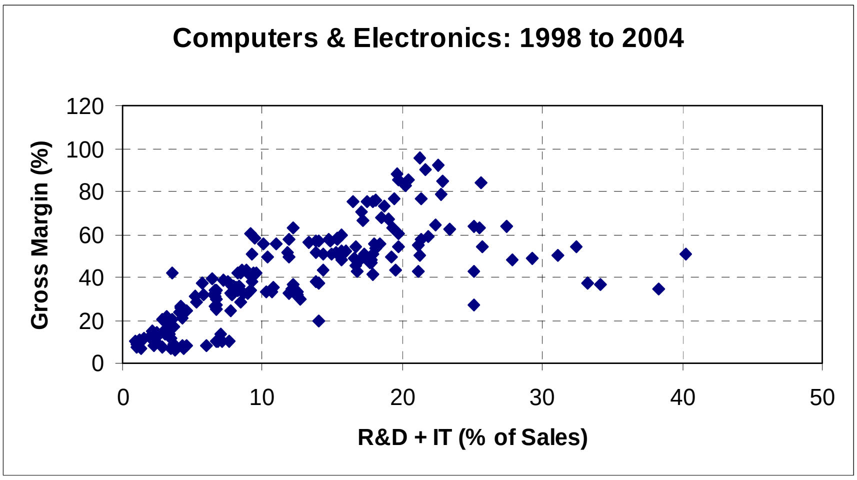

Figure 7. Firm-level R&D and IT Spending Relative to Industry Median

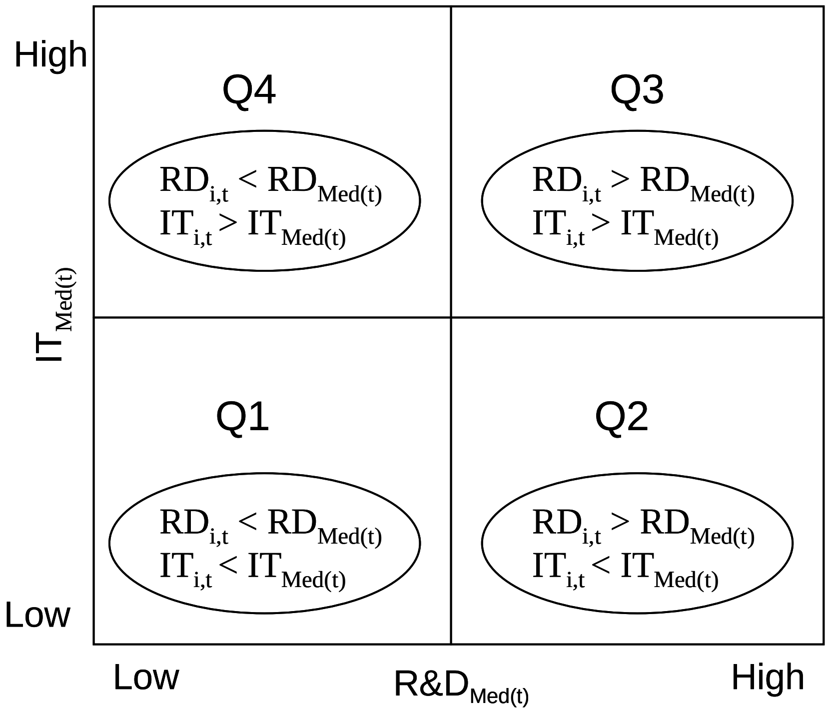

Table 1: Descriptive Statistics of the Model Variables

		R&D	IT	Sales ($M)	Assets	Advertising	Gross Margin	Operating Margin	Patents
Industrials	Mean	0.024	0.034	22,279	1.088	0.028	0.321	0.150	59
	Median	0.021	0.026	5,319	1.013	0.017	0.282	0.140	14
	Std Dev	0.018	0.050	51,223	0.378	0.036	0.131	0.056	105
	Min	0.001	0.001	83	0.322	0.000	0.067	-0.012	0
	Max	0.104	0.384	335,086	2.797	0.200	0.693	0.400	572
	75% Q3	0.032	0.0328	10,242	1.293	0.026	0.387	0.179	71
	25% Q1	0.010	0.020	2,407	0.845	0.007	0.238	0.116	0
Pharmaceuticals	Mean	0.135	0.038	17,138	1.509	0.046	0.720	0.321	86
	Median	0.128	0.037	13,177	1.351	0.042	0.765	0.304	70
	Std Dev	0.087	0.015	14,561	0.536	0.032	0.149	0.075	69
	Min	0.048	0.012	1,897	0.827	0.000	0.385	0.210	0
	Max	0.744	0.085	53,194	4.428	0.102	0.966	0.509	243
	75% Q3	0.164	0.043	22,636	1.653	0.073	0.807	0.373	149
	25% Q1	0.091	0.030	5,523	1.166	0.016	0.579	0.265	38
Computers & Electronics	Mean	0.086	0.041	13,335	1.185	0.021	0.411	0.135	215
	Median	0.066	0.033	4,142	1.006	0.014	0.418	0.120	46.5
	Std Dev	0.070	0.033	23,201	0.594	0.021	0.213	0.111	617
	Min	0.001	0.004	519	0.275	0.000	0.063	-0.267	0
	Max	0.380	0.262	110,789	3.249	0.100	0.954	0.533	3621
	75% Q3	0.140	0.051	10,560	1.474	0.028	0.548	0.176	118
	25% Q1	0.028	0.023	1,559	0.797	0.005	0.267	0.079	0
Overall Sample	Mean	0.058	0.037	18,771	1.172	0.028	0.400	0.167	114
	Median	0.032	0.030	5,526	1.069	0.018	0.345	0.147	25
	Std Dev	0.066	0.042	40,750	0.496	0.033	0.208	0.099	368

Sales from COMPUSTAT is measured in millions of dollars ($MM).

Table 2: Pearson Correlation Matrix

	RD	IT	Sales	Assets	Adv.	Patents/S	Gross Margin	Operating Margin
RD	1							
IT	0.062 (0.145)	1						
Sales	-0.089 (0.018)	-0.050 (0.239)	1					
Assets	0.540 (<.0001)	-0.011 (0.798)	0.029 (0.437)	1				
Adv.	0.070 (0.063)	-0.028 (0.515)	-0.046 (0.219)	0.005 (0.890)	1			
Patents/S	0.276 (<.0001)	-0.003 (0.951)	-0.087 (0.0211)	0.182 (<.0001)	-0.074 (0.051)	1		
GM	0.689 (<.0001)	0.036 (0.389)	-0.114 (0.002)	0.432 (<.0001)	0.390 (<.0001)	0.172 (0.0001)	1	
OM	0.376 (<.0001)	-0.055 (0.192)	0.008 (0.8277)	0.363 (<.0001)	0.315 (<.0001)	-0.135 (0.0003)	0.711 (<.0001)	1

- All variables are expressed as ratio of sales.
- *p*-values are shown in parentheses.

Table 3: Pooled Regression Results of the Main and Interaction Effects Models

		Industrials		Pharma		C&E	
2-year Lag	R&D	0.115*	0.158*	0.384*	0.688**	0.572***	0.799***
	IT	-0.041	0.063	0.109*	0.442	0.087	0.424***
	Assets	-0.097**	-0.099**	0.313***	0.333***	0.290***	0.277***
	Advertising	0.597**	0.601***	0.335**	0.357**	0.308***	0.271***
	RD x IT	-	-0.120		-0.414	-	-0.441***
	Adj. R^2	0.34	0.34	0.31	0.31	0.68	0.71
	F value	17.23 (< 0.001)	15.82 (<.0001)	4.14 (0.0001)	3.85 (0.0002)	40.75 (<.0001)	42.05 (<.0001)
3-year Lag	R&D	0.119*	0.145	0.311**	0.848***	0.557***	0.758***
	IT	-0.041	0.015	0.119	0.618**	0.083	0.340***
	Assets	-0.104**	-0.105**	0.409***	0.425***	0.302***	0.299***
	Advertising	0.606***	0.609***	0.382***	0.420***	0.302***	0.262***
	RD x IT	-	-0.067		-0.663*	-	-0.361***
	Adj. R^2	0.35	0.36	0.33	0.34	0.68	0.70
	F value	17.15 (<.0001)	15.56 (<.0001)	4.36 (0.0001)	4.23 (0.0001)	37.92 (<.0001)	37.59 (<.0001)

- *$p<0.1$, **$p<0.05$, ***$p<0.01$*
- Dependent variable is Gross Margin (expressed as a % of Sales)

Table 4: Pooled Regression Results of the Interaction Effects Model: Variations across Quadrants

		1-year Lag				2-year Lag			
		Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Industrials	R&D	-0.051	0.178***	0.068	0.161**	-0.056	0.166**	0.056	0.148**
	IT	-0.11***	-0.08***	0.019	-0.061*	-0.096***	-0.065**	0.013	-0.047
	Dummy	-0.45***	0.092	0.181**	0.193***	-0.412***	0.102	0.179**	0.184***
	Assets	-0.095*	-0.124**	-0.135**	-0.103**	-0.085*	-0.101**	-0.113**	-0.079*
	Advertising	0.603***	0.562***	0.565***	0.600***	0.616***	0.581**	0.585***	0.614***
	R&D x IT	0.254***	-0.198**	-0.168	-0.062**	0.209***	-0.197**	-0.142	-0.061*
	Adj. R^2	0.41	0.35	0.35	0.37	0.40	0.35	0.36	0.37
	F Value	18.39 (<.0001)	14.84 (<.0001)	14.96 (<.0001)	15.66 (<.0001)	17.79 (<.0001)	14.70 (<.0001)	14.83 (<.0001)	15.42 (<.0001)
Pharma	R&D	0.301	0.907***	0.390	0.350	0.233	0.636**	0.292	0.253
	IT	-0.070	0.274***	-0.100	0.004	-0.031	0.261**	-0.016	0.020
	Dummy	-0.91***	1.143***	0.235	-0.45***	-0.580*	0.975**	0.395**	-0.43***
	Assets	0.229***	0.017	0.257***	0.210***	0.365***	0.152*	0.404***	0.313***
	Advertising	0.194	-0.031	0.192	0.203	0.289**	0.061	0.312**	0.288**
	R&D x IT	0.607**	-1.08***	-0.005	0.276**	0.374	-0.79***	-0.240	0.231*
	Adj. R^2	0.40	0.58	0.30	0.33	0.36	0.53	0.34	0.37
	F Value	4.83 (<.0001)	8.99 (<.0001)	3.42 (0.0008)	3.81 (0.0003)	4.23 (<.0001)	7.35 (<.0001)	3.90 (0.0002)	4.38 (<.0001)
C&e	R&D	0.389***	0.634***	0.614***	0.585***	0.395***	0.655**	0.605***	0.587***
	IT	-0.005	0.105	0.323***	0.081	-0.055	0.050	0.252***	0.022
	Dummy	-0.42***	0.210	0.368***	0.064	-0.43***	0.206	0.342***	0.070
	Assets	0.271***	0.267***	0.190***	0.290***	0.295***	0.281**	0.223***	0.328***
	Advertising	0.288***	0.290***	0.317***	0.311***	0.295***	0.311**	0.316***	0.315***
	R&D x IT	0.201***	-0.279*	-0.48***	0.038	0.200***	-0.288**	-0.44***	0.047
	Adj. R^2	0.72	0.67	0.71	0.67	0.73	0.69	0.72	0.69
	F Value	38.65 (<.0001)	31.73 (<.0001)	37.58 (<.0001)	30.79 (<.0001)	41.35 (<.0001)	33.76 (<.0001)	38.55 (<.0001)	32.95 (<.0001)

**p<0.1, **p<0.05, ***p<0.01*; Dependent variable is Gross Margin.

Table 5: Overall Impact of RD/S and IT/S on Firm Gross Margins

	Q1		**Q2**		**Q3**		**Q4**	
	RD/S	IT/S	RD/S	IT/S	RD/S	IT/S	RD/S	IT/S
1-year Lag								
Industrials	5.524***	2.711***	-0.362	-2.838**	0.014	-0.480***	0.568	-0.425***
	17.20 (<.0001)		*8.75 (0.0031)*		*0.75 (0.3866)*		*2.89 (0.0892)*	
Pharma	3.338***	7.086**	-0.013	-6.186**	0.638	-1.058	1.318***	1.884***
	3.46 (0.0627)		*5.90 (0.0152)*		*5.00 (0.0254)*		*0.67 (0.4141)*	
C&E	3.291***	2.402***	1.051**	-4.257	0.750***	-0.789***	2.074***	0.804*
	6.88 (0.0087)		*5.66 (0.0174)*		*26.14 (<.0001)*		*6.58 (0.0103)*	
2-year Lag								
Industrials	4.688***	2.311***	-0.532	-2.785**	-0.011	-0.449***	0.508	-0.406***
	10 (0.0016)		*7.72 (0.0055)*		*0.64 (0.4230)*		*2.43 (0.1192)*	
Pharma	2.283*	4.183	-0.071	-3.687*	0.060	-1.727*	1.009***	1.758***
	1.16 (0.2811)		*2.87 (0.0900)*		*5.14 (0.0234)*		*1.83 (0.1766)*	
C&E	3.403***	2.203***	1.046**	-4.616*	0.971***	-0.976***	2.150***	0.505
	13.78 (0.0002)		*7.75 (0.0054)*		*38.63 (<.0001)*		*12.71 (0.0004)*	

- Wald-statistics for testing the coefficient differences between overall *RD/S* and *IT/S* are shown in italics.
- p-values are shown in parentheses

Table 6: Elasticity of R&D and IT spending with respect to Gross Margins

	Q1		**Q2**		**Q3**		**Q4**	
	RD/S	**IT/S**	**RD/S**	**IT/S**	**RD/S**	**IT/S**	**RD/S**	**IT/S**
1-year Lag								
Industrials	0.216	0.208	-0.039	-0.197	0.002	-0.051	0.027	-0.048
Pharma	0.570	0.441	-0.003	-0.205	0.116	-0.055	0.209	0.119
C&E	0.347	0.222	0.282	-0.195	0.179	-0.071	0.227	0.100
2-year Lag								
Industrials	0.194	0.188	-0.059	-0.205	-0.001	-0.045	0.026	-0.043
Pharma	0.374	0.291	-0.014	-0.123	0.011	-0.081	0.166	0.111
C&E	0.379	0.213	0.273	-0.224	0.230	-0.076	0.235	0.059

Table 7: Patent Count: Pooled Regression Results of the Main and Interaction Effect Models

	2-year Lag				**3-year Lag**			
	Industrials		**C&E**		**Industrials**		**C&E**	
R&D	0.352***	0.272**	0.273**	0.181	0.376***	0.299***	0.283***	0.134
IT	-0.095**	-0.288	-0.037	-0.171	-0.08***	-0.254	0.003	-0.181
Assets	-0.049	-0.047	0.133	0.139	-0.073	-0.069	0.115	0.121
R&D x IT	-	0.224	-	0.178	-	0.199	-	0.263
Adj. R^2	0.13	0.14	0.10	0.10	0.15	0.15	0.10	0.11
F value	6.37 (<.0001)	5.92 (<.0001)	3.31 (0.001)	3.10 (0.001)	6.88 (<.0001)	6.30 (<.0001)	3.15 (0.002)	3.07 (0.001)

- **p<0.1*, ***p<0.05*, ****p<0.01*. p-values are shown in parentheses; Dependent variable is Patent Count.

Table 8: Patent Count: Pooled Regression Results of the Interaction Effects Model

		1-year Lag				2-year Lag			
		Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Industrials	R&D	0.320***	0.428**	0.341***	0.324***	0.342***	0.436***	0.370***	0.351***
	IT	-0.12***	-0.11***	-0.244**	-0.12***	-0.12***	-0.09***	-0.229**	-0.114***
	Dummy	-0.075	0.503**	-0.100	-0.084*	-0.076	0.460***	-0.131	-0.063
	Assets	-0.010	-0.018	-0.009	-0.023	-0.054	-0.062	-0.045	-0.063
	R&D x IT	0.046	-0.51***	0.187	0.038	0.049	-0.44***	0.197	0.026
	Adj. R^2	**0.12**	**0.21**	**0.13**	**0.13**	**0.14**	**0.21**	**0.15**	**0.15**
	F Value	4.92 (<.0001)	8.18 (<.0001)	5.10 (<.0001)	5.02 (<.0001)	5.61 (<.0001)	8.32 (<.0001)	5.90 (<.0001)	5.64 (<.0001)
C&E	R&D	0.148	0.526**	0.145	0.233**	0.188*	0.548***	0.185**	0.262***
	IT	-0.099*	-0.16***	-0.145	-0.071	-0.085*	-0.14***	-0.153	-0.065*
	Dummy	-0.22***	-0.005	0.343***	-0.056	-0.199**	0.039	0.254**	-0.045
	Assets	0.177	0.165	0.103	0.184	0.136	0.102	0.067	0.150
	R&D x IT	0.152***	-0.44***	-0.051	0.128***	0.138***	-0.44***	0.022	0.122***
	Adj. R^2	**0.10**	**0.19**	**0.15**	**0.09**	**0.09**	**0.17**	**0.12**	**0.09**
	F-value	2.83 (0.002)	4.89 (<.0001)	3.91 (<.0001)	2.65 (0.0038)	2.63 (0.0041)	4.18 (<.0001)	3.28 (0.0004)	2.52 (0.006)

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

Table 9: Overall Impact of R&D and IT on Patent Count

		Q1		Q2		Q3		Q4	
		R&D	**IT**	**R&D**	**IT**	**R&D**	**IT**	**R&D**	**IT**
1-year Lag	Industrials	0.184***	0.010***	-0.06***	-0.37***	0.164***	-0.005**	0.149***	-0.01***
		12.36 (0.0004)		*27.23 (<.0001)*		*16.00 (<.0001)*		*16.55 (<.0001)*	
	C&E	0.369	0.217*	0.043***	-1.58***	0.057	-0.218	0.326**	0.097
		8.39 (0.004)		*17.10 (<.0001)*		*5.43 (0.020)*		*6.70 (0.010)*	
2-year Lag	Industrials	0.193***	0.013***	-0.04***	-0.32***	0.171***	-0.001**	0.146***	-0.01***
		12.99 (0.0003)		*25.17 (<.0001)*		*16.91 (<.0001)*		*17.28 (<.0001)*	
	C&E	0.374*	0.218*	0.042***	-1.508***	0.107**	-0.150	0.320***	0.094*
		9.71 (0.002)		*13.55 (0.0002)*		*4.55 (0.033)*		*7.99 (0.005)*	

- Wald-statistics for testing the coefficient differences between overall *RD* and *IT* are shown in italics
- p-values are shown in parentheses

Table 10: Elasticity of R&D and IT spending with respect to Patent Count

		Q_1		Q_2		Q_3		Q_4	
		R&D	**IT**	**R&D**	**IT**	**R&D**	**IT**	**R&D**	**IT**
1-year Lag	Industrials	0.631	0.066	-0.278	-0.969	0.969	-0.036	0.485	-0.099
	C&E	1.496	0.679	0.346	-2.917	0.225	-0.351	1.206	0.458
2-year Lag	Industrials	0.708	0.104	-0.192	-0.950	1.017	-0.003	0.499	-0.114
	C&E	1.626	0.826	0.346	-3.160	0.413	-0.226	1.228	0.414