Research Note

Business Value of Information Technology: Testing the Interaction Effect of IT and R&D on Tobin's Q

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The business case for investing in information technology (IT) has received increasing scrutiny in recent years. We propose that IT investments create additional business value through interactions with other business processes. In this paper, we formalize the interaction effect of IT by focusing on one core function, namely, research and development (R&D). We hypothesize that investments in IT can *interact with and complement* a firm's R&D investments, enhancing the firm's shareholder value creation potential. We test this by hypothesis by estimating the interaction impact of IT and R&D investments on Tobin's q, a forward-looking measure of firm performance using a recent multiyear, firm-level, archival data set. Our results suggest that the interaction effect of R&D and IT on Tobin's q is positive and significant after controlling for other firm- and industry-specific effects. Our findings provide rigorous empirical support for recent anecdotal evidence in the managerial literature with respect to the manner in which IT is enabling R&D-intensive innovation processes. Our analysis underscores the need for coordinated investments in IT and R&D, and permeating IT capabilities throughout other business processes such as R&D.

Key words: R&D; IT investments; innovation; firm performance; complementarity; Tobin's q

1. Introduction

The business case for investing in IT has received increasing scrutiny in recent years (Carr 2004, Rettig 2007). Critics point to the enormous complexity of enterprise information technology such as enterprise resource planning (ERP) software, of which the time and cost of implementing can reduce its business value. Carr (2004) argued that standard implementation of information technology can reduce a firm's strategic differentiation and "corrode" its competitive advantage. In the economics of information systems literature, the body of evidence indicates that IT improves firm productivity (Brynjolfsson and Hitt 1996) but there is no consensus on whether or how IT increases firm value. Interest in the economics of IT has moved away from macro-level benefits of IT to a debate about firm-level business value (Dos Santos et al. 2012). On one side of the debate, some have argued that firms no longer benefit from IT investments because common standards for IT infrastructure reduce the potential gains from new IT investments since competitors can duplicate a new IT application or architecture (Carr 2004, Bhatt and Grover 2005). On the other side, proponents have claimed that the value of standardized IT applications are different across firms because firms' processes and resources are not identical, and there are significant organizational and management differences in the way firms implement IT solutions (Clemons and Row 1991, Brynjolfsson et al. 2002). For example, Brynjolfsson et al. (2002) found that the financial markets treat firms' organizational structures as complementary assets with IT in a way that increases long-term output and market value.

In this study, we argue that IT investments increasingly create additional business value through interactions with other core business functions, enabling a wider range of capabilities and offerings that help meet unfilled customer needs hitherto considered not possible. We specifically focus on the R&D function and examine how investments in IT can interact with and enable a firm's R&D investments. Specifically, IT, when assimilated and integrated tightly, can help firms deliver ambitious R&D projects that involve worldwide supplier coordination and project management (Amaral et al. 2011). Similarly, IT can also help launch smart designs that leverage large volumes of information and launch products such as gene-sequence leveraging personalized medicines. We propose that the solution of difficult R&D problems and the realization of differentiated offerings through IT-enabled innovation translate into shareholder value creation for firms in a manner not recognized by the critics. Hence, it is important to study the joint effect of IT and R&D on firm performance, specifically on Tobin's q, which captures the future growth potential of firms as valued by investors.

We test IT's interaction effect by estimating the joint impact of IT and R&D investments on Tobin's q, using a recent multiyear, firm-level, archival data set that spans multiple industries. Our results suggest that the interaction effect of R&D and IT on Tobin's q is positive and significant after controlling for other firm- and industry-specific effects. These results are robust and consistent across a number of model specifications and econometric estimation methods. Our results build on recent anecdotal evidence that suggests that IT plays an important role in enabling and enhancing the productivity of R&D processes (Marwaha et al. 2007). Although recently researchers have argued that IT is changing the nature of innovation (Brynjolfsson 2010), there is a dearth of systematic empirical evidence on how IT interacts with R&D investments to enhance overall firm performance and market value. Our study represents one of the first attempts at examining the joint impact of R&D and IT on firm value using recently available data that captures the impact of newer technologies on R&D processes.

2. Background

We review the related literature as a prelude to developing a theory-based model that we test in the subsequent sections. There exists a large body of research in the information systems literature on the impact of IT on firm productivity (Barua et al. 1991, 1995; Brynjolfsson and Hitt 1996; Brynjolfsson et al. 2002; Devaraj and Kohli 2003). A complementary stream of work in economics has separately studied the effect of R&D on firm output and productivity (Griliches and Mairesse 1984, Chauvin and Hirschey 1993, Griliches 1994, Hall and Mairesse 1995). A majority of the early research on IT and firm performance has focused on the linkage between IT spending and firm- and industry-level performance. Most of these studies focused on productivity measures such as firm output (Brynjolfsson and Hitt 1996, Hitt and Brynjolfsson 1996, Barua et al. 1991), and some recent studies have focused on firm profitability measures (Aral and Weill 2007). Although earlier studies on the impact of IT on firm performance were equivocal (Rai et al. 1997, Triplett 1999), more recent ones have shown that IT plays a significant role in improving firm and industry productivity growth (Brynjolfsson et al. 2002, Bresnahan et al. 2002, Devaraj and Kohli 2003). Recent studies have also demonstrated the positive impact of IT on firm profitability using data collected during the last decade (Aral and Weill 2007, Mithas et al. 2012).

Financial market measures, such as Tobin's q, represent the ex ante market valuation of the level and risk of future firm cash flows (Ben-Horim and Callen 1989, Smirlock et al. 1984). As noted by a number of scholars, an accurate analysis of the relationship between firm-level investments and market value should examine their impact on the market-to-book ratio rather than market capitalization alone (Foray et al. 2007, Kohli et al. 2012). A financial measure such as Tobin's q, that measures the value of a firm based on its future earnings relative to current book value, is a better indicator of future growth options associated with R&D and IT spending. Tobin's q represents a forward-looking measure of firm value that takes into consideration the lag effects between investments in R&D and IT and their payoffs, and complements the retrospective firm performance captured in financial accounting measures (Kohli et al. 2012). Bharadwaj et al. (1999) showed that IT expenditures account for a significant portion of the variance in Tobin's q based on their analyses of firm-level data from 1988 to 1993.

The impact of R&D and IT on firm performance has been treated separately in a vast majority of prior studies. None of these studies have explored the interaction between IT and R&D investments and its effect on financial measures of firm performance.[1] Indeed, recent research suggests that IT has greatly improved the management of innovation knowledge through technology-enabled methods of design, prototype, testing, and knowledge dissemination (Thomke 2006). Kleis et al. (2011) focus on innovation-intensive processes to study the impact of IT on firm patent productivity and show that IT has a positive impact on firm innovation output measured as patent count and citations. Dodgson et al. (2006) and Chan et al. (2007) suggest that IT allows firms to tap into specialized

[1] Brynjolfsson et al. (2002), and more recently Tambe et al. (2012), focus on the interaction between IT and organizational practices and their impact on firm market value. Whereas their organizational constructs are based on several (survey-based) perceptual measures of organizational structure, team incentives, and worker skills, our focus on the interaction between IT and R&D investments represents a key variable of interest in our study.

knowledge across their value chain and reduce transaction costs that arise when collaborating with multiple partners in open environments. Our work also builds on the recent empirical work of Mittal and Nault (2009, p. 140) who observe that "…value from IT arises not only directly through changes in the factor input mix but also indirectly through IT-enabled augmentation of non-IT inputs and changes in the underlying production technology…." Just as R&D expenditures have been treated as an important determinant of a firm's intangible assets, researchers have started to pay more attention to intangible benefits such as improvements in quality, customer service, and strategic flexibility associated with investments in IT infrastructure (Barua and Mukhopadhyay 2000, Kleis et al. 2011, Kohli et al. 2012). Hence, our locus of interest deals with the complementarities between IT and R&D that allow firms to enhance the productivity of their R&D processes that in turn generates higher market value.

An example of the critical role of IT in enabling the performance of R&D projects is the design and development of complex aircrafts such as the Boeing 777. IT enabled paperless design of the aircraft, reduced parts and rework, and lowered the development cycle time by 20% from 60 to 48 months (Snyder et al. 1998). In Boeing's case, designers used digital product definition tools to create parts and systems as three-dimensional solid images instead of traditional two-dimensional drawings (Snyder et al. 1998). IT infrastructure enabled Boeing engineers to rapidly communicate with suppliers and manufacturing plants slashed 65% of change orders resulting in the speeding up of the process. IT usage was not limited to the product design phase. Enabling information technologies provided the backbone behind the new aircraft information management system and fly-by-wire flight control systems that made maintenance easier through fault tolerant systems. Similarly, computerized training modules and test labs for certification of aircraft and employees reduced training time for technicians from 75 to 47 days. The successful 777 allowed Boeing to compete effectively against other rivals and gain a greater share of the growing market for the next generation of aircraft. This case offers an example of the key enabling role of IT in the process of designing, developing, and launching complex products that contribute to revenue and profit growth. Hence, we argue that IT-enabled innovation provides firms with significant growth options that are typically not accounted for in *present* returns. New types of IT are expected to have far greater transformational potential compared to their predecessor systems (Aral and Weill 2007, McAfee and Brynjolfsson 2008). In this respect, both R&D and IT investments are associated with significant intangible value by enabling future growth options (Brynjolfsson et al. 2002).

3. Theoretical Framework

We now seek to understand specific mechanisms through which IT can impact firm value through its interaction and enablement of R&D processes. Information is critical to generate new knowledge in the execution of R&D projects (Kogut and Zander 1992, Nonaka and Takeuchi 1995). Henderson and Cockburn (1996) report fundamental IT-enabled changes in the way that R&D is conducted and knowledge is disseminated within firms. Recent evidence suggests that IT-enabled routines enable firms to leverage knowledge within and outside the company (Tanriverdi 2005, Tanriverdi and Uysal 2011). The impact of IT on improving R&D capabilities is felt in a number of ways, including development of component knowledge libraries, simulation tools, virtual prototypes, and product lifecycle management systems (Adler 1995, McGrath and Iansiti 1998). Firms like P&G, for instance, use virtual reality tools to replace physical mockups, enabling faster customer feedback, and reducing the cost of R&D (Bloch and Lempres 2008). New Web-based tools support collaboration by facilitating synchronous communication within and across R&D teams (Banker et al. 2006, Forman and van Zeebroeck 2012).

Prior research on IT-enabled process innovation suggests that IT contributes to the effectiveness of R&D through three primary pathways (Kleis et al. 2011). First, IT contributes to knowledge management processes used for innovation in the R&D function. Second, IT enables firms to scan the competitive environment, identify innovation opportunities, and test new types of concepts through large-scale prototyping and screening. Third, IT is an enabler of interorganizational collaboration between the focal firm and its innovation partners (Bardhan et al. 2013). Hence, we treat IT in parallel with R&D as a pervasive input, rather than simply an input to the production function. In doing so, we take into account potential interaction effects between IT and R&D and study whether such complementarities have a tangible impact on investors' assessment of a firm's future growth potential, as reflected in its Tobin's q. Ignoring such interaction effects may lead to overestimation of the effect of IT on firm market value. The use of IT to enable R&D processes also requires significant organizational changes (such as workflow redesign), and a firm's market value reflects the costs of such changes that accompany the integration of IT into R&D processes (Brynjolfsson and Yang 1999).

Our theoretical foundation draws on the IT business value framework of Bharadwaj et al. (1999) and Brynjolfsson et al. (2002) and focuses on market performance, which contrasts with that of Kleis et al. (2011) who consider patent citation count as their measure of innovation output. The empirical use of Tobin's q to capture intangible assets has been proposed by several researchers (Bharadwaj et al. 1999, Brynjolfsson and Yang 1999, Sambamurthy 2001, Kohli et al. 2012) and suggests that U.S. corporations own substantial amounts of intangible assets that are not recorded in the sector's books or reported in government statistics (Hall 2001, p. 1186). Therefore, our research focuses on how the interaction between IT and R&D creates growth options that are reflected in a firm's Tobin's q ratio.

3.1. Interaction Effect of R&D and IT on Tobin's q

Drawing upon Hall (1999) and Brynjolfsson et al. (2002), the firm market value model can be specified as a combination of firm-specific tangible assets (A_{it}), which include physical capital and labor, as well as other intangible assets (K_{it}) such as R&D investments that are valued by the market but are not included in the measured capital of the firm (Hall 1993). Hence, the market value model is expressed in Cobb-Douglas form as

$$V_{it}(A, K) = q_t \cdot A_{it}^{\sigma} t^{-\alpha} t \cdot K_{it}^{\alpha} t \cdot \varepsilon, \tag{1}$$

where α_t represents the shadow value of intangible capital and σ_t represents the overall scale effect, and ε represents the error term. Taking logarithms, on both sides, Equation (1) can be specified as

$$\log V_{it} = \log q_t + \sigma_t \log A_{it} + \alpha_t(\log K_{it}/A_{it}) + \varepsilon_{it}. \tag{2}$$

In Equation (2), the coefficient of $\log A_{it}$, σ_t, is equal to one (i.e., $\sigma_t = 1$) under constant returns to scale. Assuming constant returns to scale (as it generally is in cross-sectional data), it is possible to move the $\log A_{it}$ term to the left-hand side of the equation and estimate the following model specification:

$$\log(V_{it}/A_{it}) = \log q_t + \alpha_t(\log K_{it}/A_{it}) + \varepsilon_{it}. \tag{3}$$

We note that the dependent variable in Equation (3) is a measure of firm Tobin's q, which is expressed as a ratio of the market-to-book value of a firm's current assets. Hence, Equation (3) represents the relationship between a firm's Tobin's q and its tangible (A_{it}) and intangible assets (K_{it}).

A Tobin's q value that is greater than one indicates that the market value of the firm is greater than the book value of its current capital stock, i.e., tangible assets. Tobin's q represents a market measure of firm value that is forward looking, risk adjusted, and less susceptible to changes in accounting practices. Bharadwaj et al. (1999) assert that a major component of a firm's Tobin's q can be attributed to IT investments as manifested through its IT capabilities. Drawing upon the econometric model specified by Bharadwaj et al. (1999), we argue that a firm's Tobin's q is a function of its tangible and intangible assets, as well as firm size and the industry-specific Tobin's q, which represent industry characteristics that determine the value of firm assets.[2] Hence, we have

$$\begin{aligned} \mathrm{TOBINQ}_{it} = {} & \beta_0 + \beta_1 A_{it} + \beta_2 \mathrm{SIZE}_{it} + \beta_3 \mathrm{INDUSTRY\_Q}_{it} \\ & + \mathrm{Industry} + \mathrm{Year} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where A_{it} represents the tangible assets of the firm, SIZE_{it} represents the number of firm employees, $\mathrm{INDUSTRY\_Q}_{it}$ represents NAICS industry-average Tobin's q (corresponding to firm i's industry classification) in year t, and INDUSTRY and YEAR represent industry- and time-specific dummies. Based on arguments proposed by Bharadwaj et al. (1999) and Brynjolfsson et al. (2002), we extend the model in Equation (4) to include intangible assets as manifested in the form of IT investments. We argue that IT-enabled intangible capital leads to substantial assets that are valued by the market. Hence, our estimation model can be specified as

$$\begin{aligned} \mathrm{TOBINQ}_{it} = {} & \beta_0 + \beta_1 A_{it} + \beta_2 \mathrm{IT}_{it} + \beta_3 \mathrm{ADVT}_{it} \\ & + \beta_4 \mathrm{SIZE}_{it} + \beta_5 \mathrm{INDUSTRY\_Q}_{it} \\ & + \mathrm{Industry} + \mathrm{Year} + \varepsilon_{it}. \end{aligned} \tag{5}$$

Note that ADVT represents the level of firm-level advertising expenditures that has been shown to impact firm market value in prior research (Hall 1993). Next, we include the magnitude of R&D investment as another type of intangible asset since prior research has shown that R&D is associated with the development of firm knowledge capital and intellectual property (Hall 1993). Hence, RD_{it} and IT_{it} represents the flow of R&D and IT expenditures, respectively. As observed by Hall (1993) and Hall et al. (1986), the flow of R&D is a good proxy for long-run R&D behavior owing to the low variance of the R&D series within a firm:

$$\begin{aligned} \mathrm{TOBINQ}_{it} = {} & \beta_0 + \beta_1 A_{it} + \beta_2 \mathrm{IT}_{it} + \beta_3 \mathrm{RD}_{it} + \beta_4 \mathrm{ADVT}_{it} \\ & + \beta_5 \mathrm{SIZE}_{it} + \beta_6 \mathrm{INDUSTRY\_Q}_{it} \\ & + \mathrm{Industry} + \mathrm{Year} + \varepsilon_{it}. \end{aligned} \tag{6}$$

We then introduce the interaction effect of R&D and IT on TOBINQ. The interaction term represents the complementarity between R&D and IT in terms of the mutually reinforcing behavior of these investments on

[2] For instance, some industries have higher growth potential than others because of their product mix, and therefore it is important to control for industry-specific Tobin's q in our estimation of the impact of firm-specific intangible assets on the firm's Tobin's q.

the potential for future firm growth. The interaction effect is represented as follows:

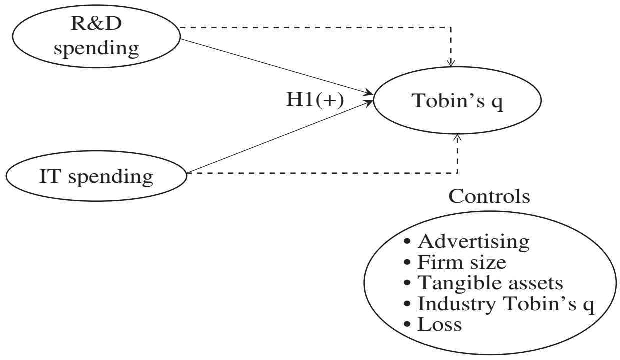
$$\begin{aligned}\mathrm{TOBINQ}_{it} = {} & \beta_0 + \beta_1 A_{it} + \beta_2 \mathrm{IT}_{it} + \beta_3 \mathrm{RD}_{it} + \beta_4 \mathrm{RD}_{it} \times \mathrm{IT}_{it} \\ & + \beta_5 \mathrm{ADVT}_{it} + \beta_6 \mathrm{SIZE} + \beta_7 \mathrm{INDUSTRY\_Q} \\ & + \mathrm{Industry} + \mathrm{Year} + \varepsilon_{it}. \end{aligned} \tag{7}$$

3.2. Research Hypotheses

IT advances are fueling a revolution in innovation through significant information processing, data analysis, and storage capabilities (Mendelson 2007, Brynjolfsson and Schrage 2009). Advances in computing allow for high-throughput screening in life sciences R&D, where lead-target drug pairs can be analyzed simultaneously, compressing the development cycle time. Our observations on the effect of IT on R&D are captured in a field study we conducted at a biopharmaceutical firm (see the online appendix available as supplemental material at http://dx.doi.org/10.1287/isre.2013.0481). Brynjolfsson (2010) argues that "…IT is setting off a revolution in innovation on four dimensions simultaneously: measurement, experimentation, sharing, and replication…." For instance, Amazon.com uses IT-based experimentation to conduct "A/B experiments" tests of its Web pages that deliver different versions of the same page at the same time to different visitors, monitor customer experience, and follow through. IT also makes it easier to replicate and scale up innovations once they have been identified. CVS Caremark Corp. identified a novel way to implement online prescription ordering at one of its pharmacies that led to a jump in customer satisfaction. CVS was able to use IT to quickly scale up this business process innovation by embedding it within an enterprise system and replicate across a network of 4,000 pharmacies within one year. IT fosters a culture of experimentation and innovation where several ideas can be tested simultaneously to study real-time changes in customer behavior. The knowledge from these experiments can be used to design new innovations that can be scaled and replicated quickly across multiple locations through digital technologies.

The IS literature has largely focused on the pathways through which IT investments create value, using the resource-based view of the firm as the dominant theoretical framework to study the direct impact of IT-enabled capabilities on firm performance (Kohli and Devaraj 2003, Banker et al. 2006, McAfee and Brynjolfsson 2008, Mithas et al. 2012, Aral and Weill 2007). However, these studies largely ignore potential complementarities between IT and R&D and their joint effect on firm performance. We argue that investments in IT are associated with higher market valuation because of growth options that are created through improvements in a firm's R&D portfolio.

Figure 1 **Conceptual Research Model**



These growth options are jointly enabled by prudent investments in R&D and IT. In our framework, IT moderates the effectiveness of R&D by providing the infrastructure that allows better management of innovation processes. Hence, we have the following:

HYPOTHESIS 1 (H1): *The interaction effect of R&D and IT investments has a positive association with firm Tobin's q.*

Figure 1 represents our conceptual research model based on the complementary effects of IT and R&D investments and their impact on firm Tobin's q.

4. Research Data

We use archival data from three sources in this study. First, we obtained multiyear, archival data on firm-level IT spending from an international research firm that is well known for its IT data and research services. This proprietary database was obtained under a nondisclosure agreement that protects the identity of the firm. The data was collected through an annual survey that was administered to chief information officers and senior IT executives of large, global firms with the goal of collecting objective metrics on IT investments. The research firm collects IT spending 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 any other costs associated with supporting the IT environment. In this study, we restrict our locus of interest to the subset of firms for which firm-level IT and R&D spending data are available for the eight years from 1997 to 2004.

Data on R&D investments as well as firm- and industry-specific financial and accounting metrics were constructed from the Standard & Poor's Compustat database. We note that the advertising data maintained in Compustat is limited because several firms do not report their advertising expenditures for a few years in our 1997–2004 panel. Hence, we supplement this data using the Taylor Nelson Sofres (TNS) Media Intelligence database, which collects firm advertising data for the period from 2002 onward. TNS is a large custom market research company and its database is widely used by researchers in marketing since it tracks spending on new media including Internet advertising expenditures.

Definitions of our model variables are provided in Table 1 and are consistent with their measurement and usage in the information systems and economics literature. TOBINQ represents the market-to-book ratio of the firm and is measured based on the definition provided in Bharadwaj et al. (1999), Kohli et al. (2012), and Perfect and Wiles (1994). IT measures the IT intensity computed as annual IT spending per employee, and R&D intensity is calculated as annual R&D spending per employee, where R&D spending includes capital and labor expenditures put to use by firms to create new products, services, or process innovations. Firm-specific control variables include the ratio of advertising expenses to sales (ADVT), the ratio of tangible assets to sales (ASSET), an indicator variable if a firm suffers accounting losses (LOSS) in a given year, and firm size measured as the logarithm of the firm's annual sales revenue (SIZE). Since there exists considerable variation in the market-to-book ratios across different industries, we include INDUSTRY_Q in our estimation models to account for industry-specific variations in Tobin's q. We construct TOBINQ and INDUSTRY_Q based on available data in Compustat.

Table 1 Variable Definitions

TOBINQ	The sum of market value of common equity (CSHO × PRCC_F from *Compustat*), liquidating value of preferred stock (PSTKL or PSTKRV if PSTKL is missing from *Compustat*) and book value of debt scaled by total assets (AT from *Compustat*) measured at the fiscal year end of year t. Book value of debt is computed as the difference between current liabilities (LCT from *Compustat*) and current assets (ACT from *Compustat*) plus inventory (INVT from *Compustat*) plus long-term debt (DLTT from *Compustat*).
R&D	R&D expense (XRD from *Compustat*) per employee in year t.
R&D (industry-adjusted)	R&D expense (XRD from *Compustat*) per employee in year t (standardized at two-digit NAICS code level by subtracting industry mean and dividing by the industry standard deviation).
IT	Firm-level IT spending per employee in year t.
IT (industry-adjusted)	Firm-level IT spending per employee in year t (standardized at two-digit NAICS code level by subtracting industry mean and dividing by the industry standard deviation).
ADVT	Advertising expense (XRD from *Compustat*) divided by sales revenue in year t.
ASSET	Tangible assets divided by sales revenue in year t. Tangible assets are computed as plant property and equipment (PPENT from *Compustat*) plus inventory (INVT from *Compustat*) plus investments and advances—equity (IVAEQ from *Compustat*) plus investment and advances—other (IVAO from *Compustat*).
LOSS	An indicator variable that equals one if the firm reports negative earnings (NI from *Compustat*) for year t.
SIZE	Logarithm of sales revenue.
INDUSTRY_Q	The median Q for the firm's industry measured at the fiscal year end of year t, based on the firm's NAICS code.

Our panel data set consists of firm-level data on the main variables of interest, namely, IT and R&D spending, as well as advertising expenditures, tangible assets, and loss indicators. Our initial sample contained 4,356 firm-year observations from 567 firms collected in the years 1997 through 2004. We removed 2,591 observations with missing IT spending in year t and 1,111 observations with missing or zero R&D spending in year t. Since we require a minimum of 10 observations per year for each two-digit NAICS industry, the size of our sample reduces to 692 observations from 189 firms (this constraint ensures that we have enough observations per industry to compute industry-adjusted R&D and IT spending measures). The resulting sample was used to compute industry-adjusted R&D and IT spending measures that we use for further analysis in our econometric estimation models. Next, we removed 17 observations with missing data for market value used in computing Tobin's q in year t. Hence, the final sample consists of 675 observations from 186 firms spanning eight years as shown in Table 2.

Table 3 provides our firm sample distribution by industry. These firms span multiple industries that include NAICS codes 32, 33, and 51. Five industry categories represent a high proportion of the firms in our sample: chemical manufacturing, metal and metal products manufacturing, machinery manufacturing, computer and electronic products manufacturing, and

Table 2 Sample Selection Methodology

	Firm-year observations	Firms
Firm-year observations obtained from the original sample covering years from 1997 to 2004	4,536	567
After		
removing those with missing IT spending data in year t;	1,945	533
removing those with missing or zero R&D spending data in year t;	834	229
requiring at least 10 observations per year for each industry at two-digit sector level using NAICS codes (the resulted sample is used to compute industry-adjusted R&D and IT);	692	189
removing those with insufficient data for computing Tobin's q in year t.	675	186

Table 3 Sample Distribution by Industry

Three-digit NAICS code	Sector	No. of firms	No. of obs.
321	Wood product manufacturing	2	3
322	Paper manufacturing	10	32
323	Printing and related support activities	2	3
324	Petroleum and coal products manufacturing	5	23
325	Chemical manufacturing	31	154
326	Plastics and rubber products manufacturing	2	2
327	Nonmetallic mineral product manufacturing	3	3
331	Primary metal manufacturing	7	23
332	Fabricated metal product manufacturing	6	39
333	Machinery manufacturing	20	64
334	Computer and electronic product manufacturing	44	156
335	Electrical equipment, appliance, and component manufacturing	11	32
336	Transportation equipment manufacturing	22	84
337	Furniture and related product manufacturing	4	8
339	Miscellaneous manufacturing	6	29
511	Publishing industries (except Internet)	10	18
518	Data processing, hosting, and related services	1	2
Total:		186	675

transportation equipment manufacturing. Hence, our sample is dominated by manufacturing firms that tend to make substantial R&D investments in order to develop new products and capabilities. Firms in the service sectors, such as retail, financial services, and hospitality industries, are generally low spenders on R&D and are not represented in our sample. We compare several measures of firm characteristics such as R&D intensity, market value, total assets, market-to-book ratio, and return on assets between our sample firms and all other firms (with nonzero R&D spending) in Computstat for each of our sample years. The results indicate that our sample firms are, on average, larger and more profitable than their peers in the Compustat universe. However, their market-to-book values are not significantly different than their peers.

We measure TOBINQ as "total firm liabilities plus liquidating value of preferred stock and total market value of common equity, divided by total book value of assets of the firm" (Hall 1999, Bharadwaj et al. 1999, p 104). We measure R&D and IT intensity by dividing the annual dollar values of R&D and IT spending by the total number of firm employees in a given year. We then standardize these values by their corresponding two-digit NAICS by subtracting the industry mean from the firm-level R&D and IT intensities, respectively, and then dividing by the industry standard deviation. Although we report the unstandardized values of R&D and IT spending in our descriptive statistics, we use only the standardized values in our econometric estimation.

We present descriptive statistics of our data set in panel A of Table 4. The mean and median values of Tobin's q are equal to 1.91 and 1.24, respectively. Similarly, the mean IT and R&D intensities are equal to \$9,871 and \$19,710 per employee. Similarly, mean advertising expenditures are approximately 1.1% of firm annual sales, and tangible assets account for 44.5% of firm annual sales on average. On average, 17.6% of firm years experienced a loss. The mean and median values of market capital (before taking logarithm) are equal to \$24,967 million and \$5,166 million, respectively, suggesting that our sample is primarily composed of large companies. The mean and median values of book-to-market ratio are equal to 0.363 and 0.349, respectively. Next, we present the Spearman/Pearson correlation matrix in panel B of Table 4. The correlation coefficients between the independent variables of interest are generally below 0.40 and do not indicate the presence of multicollinearity in our estimation models.

5. Models and Results

We now describe our econometric estimation models followed by a discussion of the results along with several robustness checks based on our model specification and estimation methods.

5.1. Econometric Estimation

We estimate the impact of firm- and industry-specific factors on Tobin's q using a series of hierarchical regression models. First, we estimate the effect of the control variables alone on Tobin's q, as specified in Equation (4). This provides a baseline estimation of the impact of the control variables on TOBINQ. Next, we include IT in the estimation equation and estimate the impact of IT on TOBINQ (along with other control variables) as specified in Equation (5). We then include the main effect of R&D as an additional variable of interest and estimate the model as specified in Equation (6). Finally, we include the interaction term $\text{IT} \times \text{R\&D}$ and estimate the model specified in Equation (7). We perform several diagnostic checks to ensure the stability of our estimation results and do not detect any significant problems (Belsley et al. 1980). We checked for multicollinearity and ascertained that the variance inflation factors were within the acceptable threshold.

In multiperiod panel data, if the population model consists of a time-invariant, unobserved heterogeneity effect (fixed effect) that is correlated with the explanatory variables, then pooled ordinary least squares (OLS) as well as random effect estimators provide regression estimates that are inconsistent. In this case, a fixed effects model may be warranted. To decide between a choice of fixed and random effects estimation models, we conduct a Hausman test to check whether the errors are correlated with the explanatory variables with the null hypothesis being that they

Table 4 Descriptive Statistics and Spearman/Pearson Correlation Matrix of Model Variables

Panel A: Descriptive statistics of model variables* ($N=675$)

	TOBINQ	IT	R&D	ADVT	ASSET	LOSS	SIZE	INDUSTRY_Q
Mean	1.910	9.871 (0.007)	19.710 (0.005)	0.011	0.445	0.176	8.501	1.300
Std. dev.	1.938	11.854 (0.998)	34.114 (0.997)	0.028	0.175	0.381	1.463	0.641
Q1	0.899	3.933 (−0.592)	3.184 (−0.540)	0.000	0.311	0.000	7.497	0.864
Median	1.243	6.023 (−0.265)	7.975 (−0.349)	0.000	0.439	0.000	8.505	1.051
Q3	2.171	11.819 (0.297)	21.713 (0.091)	0.007	0.559	0.000	9.383	1.506

Panel B: Spearman/Pearson correlation matrix

	TOBINQ	IT	R&D	ADVT	TASSET	LOSS	SIZE	INDUSTRY_Q
TOBINQ		**0.271**	**0.480**	**0.175**	−0.033	−**0.183**	*0.086*	**0.428**
IT	**0.252**		**0.384**	**0.134**	0.026	−0.015	**0.214**	*0.076*
R&D	**0.288**	**0.567**		0.012	−**0.243**	**0.193**	−**0.107**	**0.379**
ADVT	**0.218**	**0.182**	**0.186**		−**0.136**	−**0.115**	**0.121**	*0.094*
ASSET	0.026	*−0.086*	−**0.279**	−**0.140**		*−0.085*	**0.148**	−**0.236**
LOSS	−**0.320**	0.012	*0.083*	−**0.125**	*−0.093*		−**0.178**	−**0.132**
SIZE	**0.132**	**0.209**	0.064	**0.116**	0.057	−**0.169**		*−0.076*
Industry_Q	**0.479**	**0.210**	**0.403**	**0.140**	−**0.261**	−**0.132**	−**0.123**	

Notes. **Bold** values indicate correlations that are significant at $p<0.01$; *Italics* indicate correlations that are significant at $p<0.05$.

*Industry-adjusted numbers are reported in parentheses.

are not correlated. The Hausman test (Prob > chi^2 = 0.1406) does not reject the null hypothesis. If fixed effects are present, but are not correlated with the explanatory variables, pooled OLS estimation is consistent but random effects estimation models provide more efficient parameter estimates. Hence, we test whether a random effects model is warranted using a Breusch-Pagan Lagrange multiplier (LM) test. The null hypothesis of the LM test is that there is no significant unobserved heterogeneity across firms. Our LM test (Prob > chi^2 = 0.000) rejects the null hypothesis, which indicates that there exists a significant panel effect in our data. This result suggests that our use of random effects estimation models is warranted.

Having selected the regression model to obtain valid statistical inferences, we control for likely serial correlation of errors over time because of repeated measures of the same firm. Serial correlation causes the standard errors of the estimated regression coefficients to be smaller than they actually are and inflates the model R^2. We use the Wooldridge (2003) test to check for serial correlation of the errors, with the null hypothesis being that there is no serial correlation. The result (Prob > $F=0.000$) indicates significant first-order autocorrelation (AR(1)). Hence, we deploy a random effects estimation model with AR(1) errors. We estimate our models, as specified in Equations (4) through (7), using the XTREGAR procedure in the STATA software, and discuss the results of random effects estimation in the next section.[3]

Although the Hausman test does not yield a statistically significant result, the potential for endogeneity remains an important concern. We observe that management's decisions on IT and R&D spending almost certainly depends on a firm's current and future performance expectations that are reflected in firm market value. Because Tobin's q captures the firm's current and future performance expectations, an alternative explanation for the hypothesized positive relationship between IT, R&D, and their interaction effect on Tobin's q is that managers invest more in IT and R&D when there is an expectation of future growth. As a result, it is possible that our findings may be driven by reverse causality between Tobin's q to IT and R&D spending. Because causality may run in both directions, our test variables (i.e., IT and R&D) as well as some of the control variables (ADVT and ASSET) are likely to be correlated with the error term. The usual way of addressing such endogeneity issues is to estimate a two-stage least squares (2SLS) model. However, we face two problems in doing so. First, we do not have good instruments for our test variables other than their lags. With weak instruments,

[3] Random effects estimation models have also been used by Kleis et al. (2011) to estimate the impact of R&D and IT on firm-level patent innovation and productivity.

the 2SLS estimators are likely to be biased in the same way as the OLS estimators. Second, our tests for heteroskedasticity and serial correlation show significant within-firm heteroskedasticity and serial correlation in errors. This can lead to significantly biased 2SLS estimators.

We tackle this problem by using the Arellano-Bover/Blundell-Bond system generalized method of moments (GMM) estimator (Arellano and Bond 1991, Arellano and Bover 1995, Blundell and Bond 1998). The system GMM estimator produces coefficient estimates that are consistent and efficient in the presence of endogenous independent variables and fixed effects. The estimator employs a system of two equations: the original level equation and one transformed by first differencing the variables in the original equation. The first difference transform removes fixed effects. The system GMM estimator then uses the lagged values of the differences and levels of endogenous variables as instruments to control for endogeneity. Recent studies have used the system GMM model where endogeneity and fixed effects pose concerns (e.g., Aral et al. 2012). The system GMM estimation procedure controls for endogeneity and eliminates bias because of unobserved heterogeneity (Foster and Szekely 2008, Liu et al. 2010).

We use the command XTABOND2 in the STATA software to estimate the system GMM model. We include year indicators on the right-hand side of our model to remove time-related shocks from the errors. All independent variables, except for LOSS, SIZE, INDUSTRY_Q and year dummies, are considered endogenous and are instrumented with lagged values of the variables in both levels and their own first differences. We estimate the two-step system GMM estimator that is robust to patterns of heteroscedasticity and autocorrelation. Furthermore, we specify a robust option in our two-step GMM estimation to perform a Windmeijer correction to correct for any downward bias in the standard errors.

In the two-step GMM option, we specify a lag(2.) option that instructs STATA to use the second lag (and deeper lags) of the endogenous variables as instruments in the transformed equation, and the first lag for the levels equation, which represents the standard treatment for endogenous variables (Roodman 2009). In our setting, the maximum number of instruments used is 146, which does not outnumber the number of firms (186) in the panel. Our results remain qualitatively similar as we continue to drop the number of instruments used by specifying fewer lags to be used as instruments. Since we use lagged values of the differences and levels of endogenous variables as instruments for identification, the validity of the models depends on the assumption that these instruments are not correlated with the error term. This requires that the error terms (after purging fixed effects) are not serially correlated. In our case, if R&D is endogenous (i.e., RD_t is correlated with error term (t)), then our choice of $\Delta\mathrm{RD}_{t-1}$ as an instrument (where $\Delta\mathrm{RD}_{t-1} = \mathrm{RD}_{t-1} - \mathrm{RD}_{t-2}$) should not be correlated with error term (t). However, if the error term is autocorrelated (i.e., the error term (t) is correlated with error term ($t-1$)), then our choice of $\Delta\mathrm{RD}_{t-1}$ as an instrument will produce biased estimates. In such a situation, we will need to use a deeper lag. Stated differently, the precondition for the second lag to be used as an instrument requires that the error term (in levels) not be serially correlated of order one. We perform the Arellano-Bond test (1991) for autocorrelation, which has a null hypothesis of no serial correlation and is applied to AR(2) in differences to test for AR(1) in levels. The test results show no evidence of serial correlation of the errors. The Hansen test indicates whether the instruments or a subset of instruments used in the Arellano-Bover/Blundell-Bond estimation are exogenous as a group (null hypothesis). The Hansen test results suggest that the null hypothesis of exogeneity cannot be rejected, as we will discuss in the next section.

Hence, we observe that our use of two types of estimation methods (i.e., random effects and the sys-

Table 5 **Random Effects Estimation Results with AR(1) Errors**

	Predicted sign	Model 1 coefficient (z-stat.)	Model 2 coefficient (z-stat.)	Model 3 coefficient (z-stat.)	Model 4 coefficient (z-stat.)
Intercept		−0.049 (−0.09)	0.212 (0.38)	−0.333 (−0.63)	−0.395 (−0.77)
IT	+		0.301*** (4.42)	0.178*** (2.60)	0.123* (1.79)
R&D	+			0.537*** (6.44)	0.414*** (4.72)
IT × R&D	+				0.168*** (3.98)
ADVT		9.286** (2.55)	8.268** (2.34)	8.564*** (2.62)	9.334*** (2.99)
ASSET		0.409 (0.83)	0.334 (0.69)	0.821* (1.78)	0.773* (1.73)
LOSS		−0.348*** (−2.69)	−0.332*** (−2.58)	−0.472*** (−3.67)	−0.456*** (−3.55)
SIZE		0.017 (0.28)	−0.006 (−0.10)	0.059 (1.05)	0.053 (0.98)
INDUSTRY_Q		0.868*** (7.85)	0.862*** (7.90)	0.770*** (7.16)	0.829*** (7.75)
Wald χ^2 (df)		115.76 (13) ($p<0.01$)	139.96 (14) ($p<0.01$)	197.15 (15) ($p<0.01$)	226.20 (16) ($p<0.01$)
R^2 (%)		23.33	28.04	39.11	42.97
N		675	675	675	675

1. Year indicators are included in each model but the coefficients are not reported.
2. Significance of p-values are reported as follows:
$^*p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$ (two-sided tests).

tem GMM estimation models) allows us to evaluate the robustness of our results and their sensitivity to different types of estimation methodologies. Our system GMM estimation procedure for panel data follows prior research in the innovation and IT productivity literature (Liu et al. 2010, p. 1190; Aral et al. 2012, p. 12).

5.2. Results

We now present the results of our econometric estimation, followed by several robustness checks. Table 5 reports the results of random effects estimation of the impact of IT and R&D on TOBINQ. We control for year-specific fixed effects by including year dummies in all our models. The estimation results for the baseline model in Equation (4) are shown in the column labeled model 1. We observe that ADVT expenditures are associated with a positive impact on TOBINQ (coefficient $= 9.286$, $p < 0.01$), and firms that report a LOSS exhibit lower TOBINQ compared to their peers that do not report a LOSS.

Next, we report the estimation results for Equation (5) where we include the IT variable and estimate its impact on TOBINQ. We observe that IT has a positive association with TOBINQ with coefficient values of 0.301 ($p < 0.01$) as reported in the column labeled "model 2." The result suggests that a 1% increase in firm IT spending (per employee) above its industry mean is associated with a 0.301% increase in Tobin's q. We then include R&D in the estimation model and present the results in the column labeled model 3. We observe that the coefficient of IT remains significant, but its magnitude decreases from 0.301 to 0.178 ($p < 0.01$). The decrease in the magnitude of IT can be attributed to that fact that R&D represents an intangible asset that is unobserved and correlated with IT in model 2. Once R&D is included, it captures some of the variance explained by IT in the prior model. Consistent with prior studies, the coefficient on R&D is positive with a value of 0.537 ($p < 0.01$). Hence, the estimation results of the main effects of IT and R&D indicate that both variables are associated with a significant increase in Tobin's q after controlling for other firm-specific investments (such as advertising), tangible assets, firm size, and the median INDUSTRY_Q.

The last column (labeled model 4) provides estimates of the interaction effect model. The results indicate that the interaction effect is also significant with an estimated coefficient of 0.168 ($p < 0.01$) and support Hypothesis H1. In other words, a 1% increase in the interaction effect is associated with a corresponding 0.168% increase in Tobin's q. Furthermore, observe that the main effects of IT and R&D are still significant, although weaker, wherein IT is significant at p-value < 0.10 (coefficient $= 0.123$) and R&D is significant at p-value < 0.05 (coefficient $= 0.414$). The drop in the magnitudes of IT and R&D can be attributed to the fact that a portion of the variance in TOBINQ is now being captured by the interaction term, which represents a previously unobservable explanatory variable. Our results suggest that, while the main effects of IT and R&D are important, one should not overlook the interaction effect of IT and R&D. The results indicate that complementarities between IT and R&D, as manifested in their interaction effect, have a significant positive association with Tobin's q and support our hypothesis. The overall impact of IT on Tobin's q can be calculated as the sum of its direct effect and interaction effect with R&D. At the mean level of R&D spending, our results suggest that a 1% increase in IT spending is associated with a 0.12% increase in Tobin's q. Similarly, at the mean level of IT spending, a 1% increase in R&D spending is associated with a 0.58% increase in Tobin's q. The overall impacts of IT and R&D are significant, and the interaction effect accounts for a significant portion of the overall impact.

5.3. Robustness Checks

We present the results of various robustness checks to ascertain the sensitivity of our estimation results to differences in estimation methodologies and model specifications. First, we present the estimation results of the Arellano-Bover/Blundell-Bond system GMM models in Table 6. We first estimate the baseline model, followed by the estimation of the main effect of IT, and then the interaction term on TOBINQ. Consistent with our earlier random effects estimation, we observe that IT has a significant, positive association with TOBINQ with a coefficient of 0.736 ($p < 0.10$) as shown in the second column of Table 6. The results also show that the interaction effect of IT $\times$ R&D is positive and highly significant (coefficient $=$ 0.190; $p < 0.01$). Overall, the system GMM estimation results support our hypothesis with respect to the positive interaction effect of IT and R&D on Tobin's q. The system GMM results show that the interaction effect of IT and R&D on TOBINQ is positive, even after accounting for endogeneity and unobserved heterogeneity in the data.

We now present the results of a number of post-estimation tests with respect to the validity of the Arellano-Bover/Blundell-Bond system GMM estimation results, as well as the model instruments, in Table 6. The first is a test of serial correlation in the residuals. The Arellano-Bond test is applied to the residuals in differences. Since the residuals in first differences should be correlated by construction, the test evaluates second-order correlation in differences, with the idea being that serial correlation of second order in differences indicates serial correlation of first order in levels. In this case, we will need to use deeper lags

Table 6 System GMM Estimation Results for Tobin's q

	Predicted sign	Coefficient (t-stat.)	Coefficient (t-stat.)	Coefficient (t-stat.)
Intercept		−0.645 (−0.77)	0.534 (−0.59)	−2.469 (−3.06)
IT	+		0.736* (1.67)	−0.062 (−0.35)
R&D	+			0.948*** (3.15)
IT× R&D	+			0.190*** (2.56)
ADVT		17.878*** (2.68)	6.611 (0.68)	13.977*** (3.32)
ASSET		0.517 (0.30)	2.254 (1.16)	5.422*** (2.97)
LOSS		−0.285** (−2.10)	−0.344** (−2.45)	−0.693*** (−4.22)
SIZE		0.037 (0.53)	−0.044 (−0.36)	0.082 (1.04)
INDUSTRY_Q		1.100*** (2.86)	1.162*** (4.27)	0.899*** (4.49)
F-value (df)		6.82 (12,185) ($p<0.01$)	7.38 (13,185) ($p<0.01$)	54.54 (15,185) ($p<0.01$)
N		675	675	675
Diagnostic tests				
Arellano-Bond test for AR(2) in first differences (z-stat.)		−1.20 ($p=0.231$)	−1.39 ($p=0.165$)	−1.28 ($p=0.199$)
Hansen test of over identifying restrictions chi^2 (df)		55.28 (52) ($p=0.352$)	72.10 (78) ($p=0.667$)	65.47 (130) ($p=1.000$)
Difference-in-Hansen tests of exogeneity of instrument subsets				
GMM instruments				
Hansen test excluding group χ^2 (df)		42.32 (40) ($p=0.371$)	63.41 (60) ($p=0.357$)	67.00 (100) ($p=0.995$)
Difference (null $H=$exogenous) χ^2 (df)		12.96 (12) ($p=0.372$)	8.69 (18) ($p=0.966$)	−1.53 (30) ($p=1.000$)
Exogenous variables				
Hansen test excluding group χ^2 (df)		42.01(42) ($p=0.470$)	68.76 (68) ($p=0.451$)	61.65 (120) ($p=1.000$)
Difference (null $H=$exogenous) χ^2 (df)		13.27 (10) ($p=0.209$)	3.34 (10) ($p=0.972$)	3.82 (10) ($p=0.955$)

1. Year indicators are included in each model but the coefficients are not reported.
2. We report two-step estimators, which are asymptotically efficient and robust to any panel-specific autocorrelation and heteroscedasticity. We correct for the downward bias in the standard errors using the Windmeijer correction.
3. Significance of p-values are reported as follows:
$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$ (two-sided tests).

as instruments. Table 6 shows the results of AR(2) tests of the null hypothesis that indicate that there is no serial correlation in second differences of residuals. The AR(2) test yields p-values of 0.231, 0.165, and 0.199 for the three models, respectively.

Next, we present the results of the Hansen (1982) test of overidentification conducted as part of our system GMM estimation. The system GMM estimator uses multiple lags as instruments. This means that our system is overidentified and provides us with an opportunity to conduct a test of overidentification that tests whether the instruments are exogenous. Table 6 shows the results of the Hansen test of the GMM estimates. The Hansen test yields a J-statistic that has a χ^2 distribution under the null hypothesis that the instruments are orthogonal to the error term. The results shown in Table 6 reveal z-statistics with p-values of 0.352, 0.667, and 1.000 for the three models, respectively, which indicates that we cannot reject the null hypothesis.

Table 6 also reports the results of a test of exogeneity of a subset of our instruments. The system GMM estimator makes an additional exogeneity assumption that any correlation between the endogenous variables and the unobserved (fixed) effect is constant over time. This assumption allows us to include levels equations in our GMM estimates and use lagged differences as instruments for these levels. Bond et al. (2001) suggest that this assumption can be tested directly using a difference-in-Hansen test of exogeneity. The null hypothesis suggests that the subset of instruments that we use in the levels equations is exogenous. The p-values associated with the Hansen test in Table 6 imply that we cannot reject the null hypothesis that the additional instruments in the system GMM estimation are exogenous.

Next, we test the sensitivity of our results to alternative measures of IT and R&D intensity. We compute IT and R&D intensities as IT and R&D spending scaled by annual firm sales, respectively, and then rerun the random effect models with AR(1) errors. The results, as reported in Table A1 of the online appendix, are qualitatively similar to our estimation results reported in Table 5. We observe that the main effects of both IT and R&D have a positive and significant association with Tobin's q, and the interaction effect of IT x R&D is positive and significant at $p < 0.05$. We also note that IT by itself has a significant direct impact on TOBINQ (coefficient $= 0.216$, $p < 0.01$). Introduction of the interaction term weakens the main effects of IT and R&D, although they continue to remain significant, and the interaction effect has a positive association with TOBINQ. This indicates that firms that exhibit higher levels of IT and R&D spending are likely to reap the benefits of their complementarities through greater valuations as reflected in higher Tobin's q.

Furthermore, we deploy an alternate measure of Tobin's q to evaluate the sensitivity of our results to the manner in which it is defined. Following Lang and Maffett (2011), we define Tobin's q as the value of a firm's total assets plus market value of equity minus the book value of equity scaled by total assets.[4] Our results using the alternate definition of Tobin's q are similar to the results reported in Tables 5 and 6, and indicate that the interaction effect of R&D and IT is positively associated with Tobin's q. Hence, our results suggest that they are not sensitive to alternate definitions of Tobin's q. We note that the observed complementarities between IT and R&D represent equilibrium and not causal relationships and our study findings highlight an important pathway through which IT can impact firm business value.

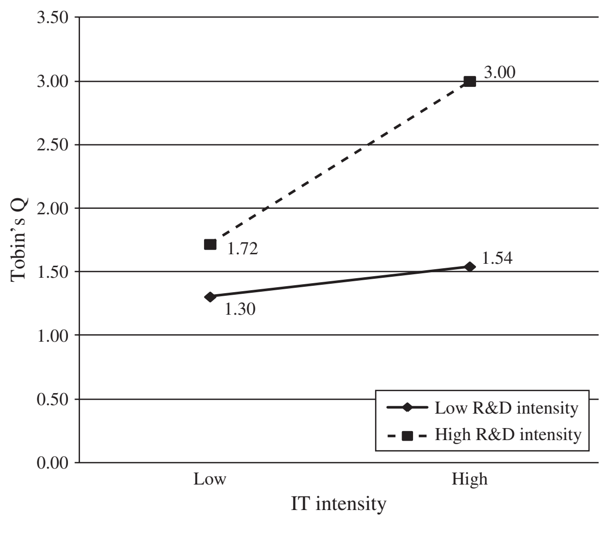
[4] The alternative measure of Tobin's q includes noninventory current assets in the calculation of current liability, whereas we exclude such assets from current liabilities in our Tobin's q calculations as reported in the paper and used in our econometric estimation models.

6. Discussion

To test whether there exist significant differences between firms in their usage of IT in innovation activities, we split our sample of firms based on their IT intensity values. We measure IT intensity as the ratio of IT spending to firm output (sales). Our split sample analysis is similar to the approach described in Dewan and Min (1997), Mittal and Nault (2009), and Han et al. (2011), who use IT intensity to differentiate between IT-intensive and non-IT intensive industries. Figure 2 represents a two-dimensional plot of the differential effect of the impact of IT and R&D on TOBINQ. On the X-axis, we plot IT intensity where we classify a firm as "low IT intensive" or "high IT intensive" depending on whether its IT intensity is lower or higher, respectively, than the median IT intensity of other firms in the same three-digit NAICS code during the period of our study. We use a similar approach to classify firms into "high R&D intensive" and "low R&D intensive" groups based on their magnitude of R&D intensities relative to industry peers. The Y-axis represents the dependent variable of interest, TOBINQ.

We then plot the TOBINQ values of all firms in the "low R&D intensity" group as shown by the solid line in Figure 2. Similarly, we plot the TOBINQ values of all firms in the "high R&D intensity" group as depicted by the dotted line. We observe a significant difference in the TOBINQ values of firms that fall on the "low IT intensity" end as compared to firms on the "high IT intensity" end of the plot. High R&D intensity firms that exhibit low IT intensity have an average Tobin's q of 1.72, whereas firms with high R&D *and* high IT intensity exhibit an average Tobin's q of 3.00. These effects are pronounced even among firms that are in the low R&D intensity

Figure 2 **Interaction Effect of IT and R&D on Firm Tobin's q**



group where Tobin's q increases from 1.30 for low IT-intensity firms to 1.54 for high IT-intensity firms.

A split sample analysis using the same econometric estimation methods described in the previous section confirm that the interaction effect of R&D and IT on Tobin's q is positive and significantly stronger within "high R&D" firms compared to the "low R&D" firms. The split-sample regression estimation results are shown in Table A2 of the online appendix. These results suggest that the complementary effect of IT and R&D on TOBINQ is prevalent among firms that invest in R&D and IT processes at levels that are greater than their industry peers, and are therefore able to effectively leverage IT investments to complement their R&D processes to drive innovation. In this respect, IT serves as an enabler of growth in R&D-intensive firms as evidenced by their higher market valuations.

Since our study spans a unique period in financial markets that encompass the dot-com boom of the late 1990s and the bust of the early years of the 21st century, we investigate whether our results are influenced in any way by the volatile nature of the financial markets during this period. We split our sample into two groups that consists of 257 firm-year observations in the 1997–1999 subsample, and 418 firm-year observations in the post-year 2000 subsample, and estimate our regression models for these two subsamples separately. We observe that the main and interaction effects are similar to our earlier results reported in Tables 5 and 6. Specifically, we note that the coefficient of the interaction effect is somewhat stronger in the post-year 2000 period (coefficient $= 0.33$, $p < 0.01$) as compared to the pre-year 2000 period (coefficient $= 0.11$, $p < 0.10$). Hence, we conclude that the complementary effects of IT and R&D are observed consistently across a relatively long period of eight years, and their effects are pronounced among R&D-intensive firms. Our results are consistent with recent research by Dos Santos et al. (2012) who report that opportunities for firms to use IT to improve their performance are not diminishing.

7. Conclusions

In this study, we have focused on the role of the *IT enablement effect* on R&D processes and their impact on firm Tobin's q. Quantum strides in computing have been made during the IT revolution since the early 1990s, and it is important to (a) understand the specific role of IT in improving the effectiveness of R&D processes, and (b) measure the joint impact of R&D and IT investments on firm market value. Although the literature has focused on the direct/main impact of IT spending, our study focuses on the critical question: "Do complementarities between IT and R&D spending increase firm market valuation?"

We propose and empirically test our research model using a relatively recent data set that reflects significant technological changes in knowledge-based industries since the first wave of Internet-based, commercial technologies in the late 1990s. Our study confirms that IT spending has a positive impact on firm Tobin's q. In addition, our results indicate that IT interacts with R&D investments, and this interaction effect is positive and has a significant impact on firm Tobin's q as observed in our relatively large sample of firms studied across a time period that spans the pre- and post-year 2000 phenomenon. Whereas prior research has focused solely on the individual effects of R&D and IT, our results reveal a new dimension by measuring the interaction between these two types of complementary investments. These results support our hypothesis with respect to the positive, complementary effects of R&D and IT on Tobin's q, and provide empirical evidence to refute recent anecdotal observations in the practitioner literature that question the value of R&D and IT investments (Kandybin and Kihn 2004, Carr 2004). Hence, our research contributions are twofold: (a) we propose a theoretical framework to study the IT enablement effect on R&D and innovation-intensive processes, and (b) we provide an empirical test of the interaction effect of IT and R&D investments on Tobin's q, a financial measure of shareholder value.

In this attempt to break new ground in the study of IT-innovation interactions, our work has several limitations. First, we acknowledge that the observed complementarities between IT and R&D investments represent equilibrium relationships that represent interesting phenomena and warrant further research into the types of IT systems that help firms realize greater value from R&D assets (Bloom et al. 2012). Second, 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 including their allocation between various components of IT spending such as hardware, software, and consulting (e.g., Harte-Hanks data on Fortune 1,000 firms). Third, since product development times in some industries are long, 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. Fourth, we use data on large, global firms that are primarily involved in manufacturing and report tangible R&D investments. This limits generalization of our findings to similar firms, and further exploration with data from other industries is needed. We acknowledge that these represent missing variables that can potentially affect our results, and further research is needed with additional data to improve our understanding of the complementarity effect of IT and R&D spending on firm performance. Future field studies in industry-specific settings are also needed to develop greater visibility into the pathways through which firms can harness the power of R&D and IT to improve their innovation capabilities.

The findings of our study suggest that IT can play a critical enabling role in helping to increase the impact of R&D investments and enhancing firms' market value. From a managerial perspective, an important implication of our study is to focus on coordinating investments in IT and R&D and using IT to improve innovation processes and outcomes. Opportunities to use IT in all phases of the product and process innovation lifecycle should be explored. From a research dimension, our study provides a fresh perspective into the drivers of firm financial performance and provides a new pathway that explains how IT can moderate the impact of R&D on firm market value. It addresses a gap in the literature that has heretofore ignored the possibility of interaction effects when studying the relative impact of IT and R&D on firm performance. We propose that coordinated investments in R&D and IT provide firms with greater capacity to generate future growth options that help to realize market value.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/isre.2013.0481.

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