Information Technology and Intangible Output: The Impact of IT Investment on Innovation Productivity

Landon Kleis, University of British Columbia
landon.kleis@sauder.ubc.ca

Paul Chwelos, University of British Columbia
paul.chwelos@ubc.ca

Ronald V. Ramirez, University of Colorado, Denver
ronald.ramirez@ucdenver.edu

Iain Cockburn, Boston University
cockburn@bu.edu

Forthcoming at Information Systems Research (accepted July 25, 2010)
http://www.informs.org/Pubs/ISR/Future-Issues

Abstract

Prior research concerning IT business value has established a link between firm-level IT investment and tangible returns like output productivity. Research also suggests that IT is vital to intermediate processes like those that produce intangible output. Among these, IT's use in innovation and knowledge creation processes are perhaps the most critical to a firm's long-term success. However, little is known about the relationship between IT, knowledge creation, and innovation output. In this study, we contribute to the literature by comprehensively examining IT's contribution to innovation production across multiple contexts, using a quality-based measure of innovation output. Analyzing a panel of large U.S. manufacturing firms between 1987 and 1997, we find a 10% increase in IT input is associated with a 1.7% increase in innovation output for a given level of innovation-related spending. This relationship between IT, R&D and innovation production is robust across multiple econometric methodologies and found to be particularly strong in the mid to late 1990s, a period of rapid technological innovation. Our results also demonstrate the importance of IT in creating value at an intermediate stage of production, in this case, through improved innovation productivity. However, R&D and its related intangible factors (skill, knowledge, etc.) appear to play a more crucial role in the creation of breakthrough innovations.

Keywords: information technology, productivity, knowledge production function, innovation, patents, research and development, IT business value, breakthrough innovation

Acknowledgements: This research has been supported by grants from the CISE/IIS/CSS Division of the U.S. National Science Foundation and the NSF Industry/University Cooperative Research Center (IUCRC) to the Center for Research on Information Technology and Organizations (CRITO) at the University of California, Irvine, as well as the Social Sciences and Humanities Research Council of Canada (SSHRC) and the UBC Hampton Fund. Industry sponsors to CRITO include: ATL Products, Boeing, Canon Information Systems, Conexant Systems, IBM, Microsoft, Nortel Networks, Seagate Technology, Sun Microsystems, and Whirlpool.

1. Introduction

Innovation is a key contributor to a firm's competitive success. Product innovations can enable a company to earn abnormal profits as well as provide an avenue for expansion into new markets and industries (Roberts 1999; Agarwal and Bayus 2002). Process innovations create new methods of performing firm activities that can reduce costs or generate new lines of revenue growth (Baily and Chakrabarti 1988; Dougherty and Hardy 1996). Together, these benefits motivate firms to invest in the innovation process.

In recent decades, new information technologies and their widespread application have led to three evolutionary changes in the innovation process (Quinn et al. 1997). Information technologies like communication and database applications have helped improve *the management of innovation knowledge*. Researchers, for example, distributed across company research centers can now share knowledge assets across remote geographies and time (Thomke 2006). *Innovation production* has been improved through IT-based digital methods of design, prototype, and test (Sudarsan et al. 2005; Thomke 2006). IT-based networks and real time data flows enable *external innovation collaboration* (Thomke 2006). Through the outsourcing of innovation production elements (design, prototype development, test, etc.) firms gain access to specialized knowledge and other innovation components that can be incorporated into new products, services, and processes (Chan, Nickerson and Owan 2007). The application of information technologies provide the links necessary for effective information sharing and partner monitoring, as well as reduce transaction costs that arise when working with multiple innovation partners in an open environment (Dodgson, Gann and Salter 2006; Thomke 2006; Brockhoff 1992).

In short, through the management of knowledge assets, production support, and inter-organizational coordination, information technologies have improved the speed and efficiency of firm innovation. As a result, IT has become essential to product development in firms, especially those in the automobile, consumer products, apparel, and textile industries (Sangiovanni-Vincentelli 2003; Teresko 2004; Istook 2000). Yet despite the ability of IT to improve the innovation process, innovation remains a costly and risky endeavor. One estimate puts the failure rate of new products at over 90 percent (Brown and Eisenhardt 1995). Does this imply that collectively, information technology has little impact on the firm innovation process? If the innovation creation process remains uncertain and firms run the risk of receiving little or no benefit from these activities, should firms continue to invest in innovation-related IT?

We investigate these research questions by building upon existing preliminary work that considers the relationship between information technology and innovation output (Kleis et al. 2003; Han and Ravichandran 2006). Specifically, we contribute to the literature by applying the knowledge production function to (1) evaluate IT's role in innovation creation across a more extensive time frame; (2) introduce a quality-adjusted measure of innovation output, enabling the evaluation of IT's contribution to quality innovation; and (3) conduct an in-depth analysis that provides a richer understanding of the IT-innovation relationship. This includes the examination of how the role of IT evolves over our sample period, how IT's contribution varies across industries that produce versus use IT, and finally, whether IT plays a role in the development of both incremental and breakthrough innovations.

In this study, we utilize a unique dataset comprised of annual information on innovation spending (R&D), IT spending, and citation-weighted patents (a quality-adjusted measure of innovation output) for large U.S. firms between 1987 and 1997. We analyze over 1,800 observations using a robust set of econometric methods to test the relationships between IT, R&D, and innovation performance. Our econometric estimates indicate that IT capital has a positive and significant effect on knowledge output. We find a marked increase in the contribution of IT to innovation in the early to late 1990s. However, the evidence does not suggest a significant role for IT in the creation of breakthrough innovations. Rather, as highlighted in existing research, non-IT factors (strategic orientation, organization practices, R&D management, etc.) may hold the key to innovation leadership (Enkel, Gassmann, and Chesbrough 2009; Majchrzak et al. 2005; Malhotra et al. 2001; Balachandra and Friar 2002). Nonetheless, the core result remains; information technology makes a consistent, positive contribution to the innovation creation process.

The remainder of the paper is organized as follows. In the next section, we review theory related to information technology and innovation creation. In section 3, we discuss our research design, methodology, and data, followed by a discussion of our empirical analysis and results in section 4. We provide a discussion of our findings and a conclusion in sections 5 and 6.

2. Theory

Firms pursue innovation to build or maintain competitiveness. This is accomplished through the creation of productivity-improving value chain activities (process innovations) or through the extraction of rents generated by the sale of new products or services (product innovations). Preliminary research has identified information technology as a potential contributor to firm innovation efforts. In particular, Kleis et al. (2003) proposed a knowledge production function framework to perform a preliminary test of the IT-innovation relationship. Their analysis found no conclusive results. Han and Ravichandaran (2006) test a similar model using panel estimators, and find evidence of an indirect IT-innovation relationship (interaction of R&D and IT). Our study builds upon this nascent work and provides a value-added and thorough examination of IT's role in innovation by using a more extensive time frame, a more complete measure of innovation output, and a more comprehensive evaluation of the direct IT-innovation relationship across multiple contexts. We now explicate the theoretical underpinnings of IT's role in knowledge production.

2.1. Innovation

Technological innovations are created when a new idea or concept is transformed into a product or process for internal or commercial use (Baily and Chakrabarti 1988). Process innovations are changes to existing processes or the creation of new processes used by an organization to deliver products or services. Product and service innovations are new products or services introduced into the marketplace (Dibrell et al. 2008). Innovations can arise from raw ideas borne within the firm or result from the adaptation of new knowledge found outside of the firm. This includes basic scientific knowledge generated by corporate and university laboratories, as well as inventions spawned by other firms.

Firm innovation proceeds in two stages: first, *research* is conducted to create or determine the efficacy of an invention in addressing some identified problem. Next, the firm undertakes *development* activities related to readying the proposed product or process for its production or application, including design and testing. The Federal Accounting Standards Board (FASB) definition of research and development activities mirrors this two-stage process, making R&D expense a good measure of invention and innovation activity in U.S. firms.[1]

To model innovation, we adopt a theoretical model from earlier research in economics and R&D literature (Pakes and Griliches 1984). The knowledge production function (KPF) represents the knowledge output generated by a firm as a function of inputs used in its innovation process. We augment the traditional KPF with an information technology input to reflect our notion that information technology contributes to the production of knowledge in a firm. Like the "black box" in production theory, the innovation creation process is inherently unobservable.

2.2. IT and the Innovation Process

The application of IT contributes to the innovation process through three primary mechanisms. First, information technology contributes to the management of knowledge used in innovation production. Second, information technology enables critical elements of the innovation production process including opportunity identification, concept development, and innovation design. Third, information technology enables the inter-organizational coordination between the focal firm and its external innovation partners.

2.2.1. IT and Innovation Knowledge Management

The management of knowledge is an activity critical to the creation of new innovations. Research and development knowledge, combined with operations knowledge is used by a firm to develop and produce new products and services (Tanriverdi 2005). Information technology helps to create an

[1] FASB Statement of Financial Accounting Standards No. 2 and No. 86 provide a definition of research and development. Research is defined as a planned search or critical investigation aimed at the discovery of new knowledge with the hope that such knowledge will be useful in developing a new product or service, or a new process or technique, or in bringing about a significant improvement to an existing product or process. Development is defined as the translation of research findings or other knowledge into a plan or design for a new product or process or for a significant improvement to an existing product or process whether intended for sale or use. See FASB statements No. 2 or 86 for full definitions, http://fasb.org/st/.

infrastructure for capturing and sharing knowledge across the enterprise on a scale previously unattainable (Tanriverdi 2005; Majchrzak et al. 2004; Lee and Choi 2003). The participants involved in the innovation process are interconnected by a knowledge network, sharing, combining, and reusing knowledge in the creation of new goods and services (Nerkar and Paruchuri 2005). Each participant has a specific skill or knowledge which he or she contributes to the innovation process, either directly to the item being created or indirectly through the transfer of knowledge to other actors who then apply it directly in the innovation process. At times, gaps can arise in the knowledge network from links that are missing between participants or from a knowledge element that is missing but is necessary for the innovation process to generate value-added output (ibid.). Information technology helps close these knowledge gaps by enabling the collection of new knowledge assets through improved search capabilities and data mining techniques. Information technology also enables the interconnection of participants who may not be directly involved with the network, but who can temporarily be connected in order to provide a valued knowledge asset that will contribute to the innovation effort. New technologies help to capture internally generated knowledge that can be used throughout the innovation process. The electronic laboratory notebook (ELN), for example, enables scientists to capture and record experiment data electronically versus traditional paper-based lab books, improving efficiency and eliminating transcription errors (Elliott 2006). The ELNs help to create a central repository of data accessible by other scientists and other drug development systems.

Front end technologies can also be used to capture innovation-related knowledge. Customer data used in new product development, for example, is captured through company retail websites and through other communication technologies (e.g., email, telecommunication systems) utilized in customer contact interactions (Zahay et al. 2004). These data enable a firm to develop in-depth knowledge of its customers and create new innovations that better fit customer needs. In the end, this increases the value of a firm's products to its customers and ultimately, customer satisfaction (Mithas, Krishnan, and Fornell 2005a, 2005b).

After new knowledge is collected, information technology is critical for the sharing and reuse of knowledge throughout an enterprise (Lee and Choi 2003). Corporate IP-based networks, telecommunications and email systems all facilitate the transfer of knowledge between innovation participants. Email, for example, has been shown to be an effective communications and information sharing tool between participants in an R&D network (Rice 1994). These technologies also provide the infrastructure for facilitating the virtual, interpersonal interactions among R&D teams that ensure the transfer of both explicit and tacit knowledge (Lee and Choi 2003; Rice 1994).

External knowledge is also critical for successful innovation. The transfer of external knowledge used in the innovation process can take place through the acquisition of new knowledge, licensing of external innovations, acquisition of firms with unique knowledge, and the hiring of experts with relevant knowledge (Cassiman and Veugelers 2006). General infrastructure IT (e.g., PCs, email, etc.) can assist in this type of knowledge acquisition (Cassiman and Veugelers 2006). Network and internet-related communications technologies, for example, have increased the flow of and access to scientific information contained in electronic versions of scholarly journals and public research databases, both of which are important to the R&D process (Kremp and Mairesse 2004). Computer networks and online access are also critical for the discovery and sharing of competitive and regulatory factors that must be incorporated into new product development innovations (Zahay et al. 2004). IT-based knowledge sharing was the case at Aventis, a major pharmaceutical manufacturer, where the implementation of a chemical biology platform enabled the sharing of knowledge between the virtual community of drug discovery project teams, resulting in a more productive innovation process (Narayanan et al. 2004).

The benefits of IT-enabled innovation have been demonstrated in an academic setting (Hamermesh and Oster 2002; Agrawal and Goldfarb 2008). Indeed, the decreasing costs of IT and subsequently, the costs of communicating and sharing innovation-related knowledge information is motivating an increased use of IT in academic innovation networks (Agrawal and Goldfarb 2008). Email, fax, and telecommunication technologies, for example, have enabled distributed innovation teams to complete new academic research valued by the economics research community (Hamermesh and Oster

2002). The use of Bitnet, a cooperative U.S. university network predating the internet, increased the use of multi-institutional partnerships and participation of new actors in university engineering research (Agrawal and Goldfarb 2008). In summary, whether in a business or academic setting, information technology supports the interactive flow of knowledge between networked participants involved in innovative activity (Swink 2006; Horn 2005; Brennan and Dooley 2005).

2.2.2. IT and Innovation Production

Firms apply and utilize knowledge within an innovation process to produce new products and services. Innovation production has evolved over time from a linear, push oriented process, to a parallel design that incorporates customer and supplier input (Rothwell 1994). Schilling and Hill (1998) model innovation production as a series of five activities that can occur in parallel, and include opportunity identification, concept development, product design, and commercial production. Similarly, Rothwell (1994) models innovation production as six parallel and integrated activities that include marketing, R&D, product development, production engineering, parts manufacturing, and product manufacturing. Although there are slight differences in these models, this research indicates that innovation production involves idea and concept development (new technologies, needs analysis), product development (design); engineering (prototyping), and manufacturing.[2]

Information technology contributes to innovation production in multiple stages. In the idea stage, customer relationship management systems act as an information input to innovation production. The information flowing from CRM systems enables a firm to analyze its customers and identify needs that are not being met by current products and services (Nambisan 2002). This helps the firm generate new product ideas that account for unmet or evolving demand side factors and contributes to new product success (Rothwell 1994; Naver, Slater, and MacLachlan 2004; Mithas, Krishnan, and Fornell 2005, 2005a).

---

[2] Consistent with research (Rothwell 1994, Schilling and Hill 1998, Tatikonda and Rosenthal 2000) and the majority of awarded, patented innovations, we focus our process discussion on product innovation.

Information technology also enables efficient design capabilities. Technology like computer based design applications (e.g., CAD/CAM systems) help to digitize a new product's design and make it available throughout the innovation production process. This allows team members to integrate their design efforts, whether located in local or distant R&D centers, from product conception through final assembly (Sudarsan et al. 2005; Gordon et al. 2008; Bartholomew 2005). Computer based design software also allows team members to develop virtual prototypes. Engineers can use digital prototypes to run computer simulations to test component compatibility, overall workability, and failure analysis. Digital-based prototypes and simulation, like those used in automobile, computer, and pharmaceutical manufacturing, not only reduce the cost of traditional wood and clay methods, but allow prototypes to be developed and used much earlier in the innovation production process (Rothwell 1994). This allows poor designs to be filtered out much earlier in the process and improves overall innovation process efficiency (Thomke 2006; Rothwell 1994).

Finally, IT is being used to integrate design and production systems, enabling greater precision and overall product introduction efficiency (Hatch and Mowery 1998). The use of software-based manufacturability testing, for example, can help designers identify the most efficient ordering of parts that should be used during the manufacturing of final products (Konicki 2002). CAD systems improve the linkages between design and manufacturing, helping to integrate the two departments, reducing errors of information transfer and translation (Rothwell 1994). This serves to minimize manufacturing costs as well as improve the efficiency of production throughput for the new innovation.

2.2.3. IT and External Innovation Collaboration

The production of new innovations involves collaboration between team members working together to create new products, services, or processes. The distributed team shares a common goal of innovation creation with each member adding value to the innovation under production (Majchrzak et al. 2005). Traditionally, this process occurred within the firm's boundary, and thus required the acquisition and development of innovation-related inputs. However, a shift in innovation practices occurred in the 1980s when firms began to source some of these inputs externally (Rothwell 1994). As a result, team membership expanded to encompass internal and external participants, in both local and geographically distant sites.

Many factors have motivated the inclusion of external partners in innovation. These include the complexity and pace of industrial and technological change, global competition, greater range of available innovation partners, and the mobility and global availability of knowledge workers (Dodgson et al. 2006; Rothewell 1994; Enkel et al. 2009). The result has been an opening up of the firm's boundary and the creation of an integrated innovation network involving the focal firm, customers, suppliers, and other sources of new knowledge (Dodgson et al. 2006; Enkel et al. 2009; Christensen et al. 2005). The movement toward a more open innovation process has had an effect on the propensity of a firm to innovate and helped improve the fit of new products and the overall efficiency of innovation (Dodgson et al. 2006; Enkel et al. 2009; Schilling and Hill 1998).

Information technology is a critical enabler of collaborative innovation, providing the necessary linkages for information exchange with external partners. Infrastructure technologies like personal computers, laptops, data and voice networks, and communications applications (e.g., email) are instrumental to these collaborative efforts (Majchrzak et al. 2005, Enkel, Gassmann, and Chesbrough 2009). These technologies facilitate the exchange of information to and from external participants in the innovation partnership. In an aerospace manufacturer, for example, specialized web interfaces were created to enable company team members to exchange information with external team participants (Malhotra et al. 2001). In 54 innovation teams across 15 industries, including manufacturing, basic infrastructure technologies (e.g., networks, email, NetMeeting, etc.) were utilized as a communication infrastructure for the exchange of information across the teams, including members external to the firm (Majchrzak et al. 2005). Indeed, from the focal firm perspective, information and communications technologies play a critical connectivity role in the open innovation era (Dodgson, Gann, and Salter 2006; Enkel, Gassmann, and Chesbrough 2009).

Beyond connectivity, information technology plays an important role in creating an effective partnership between a firm and an external service provider. In today's open innovation process, a focal firm can choose to hire and work with an external organization to outsource innovation activities like design, component development, and test (Dodgson, Gann, and Salter 2006; Nellore and Balachandra 2001). In such situations, the use of information technology enhances the relationship between the firm and service provider and contributes to partnership success. Indeed, in IT outsourcing and other collaborative relationships, the deployment of information technology has been shown to have a positive effect on communication, trust, and shared understanding, contributing to the success of the business relationships (Ryssel et al. 2004; Paulraj et al., 2008; Malhotra et al. 2001; Ba and Pavlou 2002). Research in an innovation setting found inter-organizational technologies have a positive effect on external new product development relationships in disk drive manufacturing (Scott 2000). In the long run, such effective innovation relationships produce value-added inputs to a focal firm's innovation process. Ultimately, these value-added inputs contribute to successful innovation production (Dodgson, Gann, and Salter 2006; Nellore and Balachandra 2001).

In summary, information technology contributes to the firm innovation process by enabling innovation knowledge management, innovation production, and external innovation collaboration. The end result is a collaborative innovation process, enabled through IT, that creates new value-added innovations in a productive manner. Indeed, Kortum and Lerner (1998) conclude after examining innovation production from the 1990s onward, the rise in innovation output (measured in patenting activity) is mainly due to the application of new information technologies developed during the same time period. Thus, it is reasonable to expect a relationship between information technology and the innovation production process (Lee and Choi 2003).

3. Research Design and Methodology

Our conceptual model of knowledge production, based on the Knowledge Production Function (Pakes and Griliches 1984), is presented in Figure 1. Consistent with existing literature, research and development activity is a primary input to knowledge production in a firm (Hall et al. 1986; Henderson and Cockburn 1994; Hall and Mairesse 1995; Madsen 2008). To incorporate the proposed role of information technology in innovation, we introduce information technology as an additional input to knowledge production.

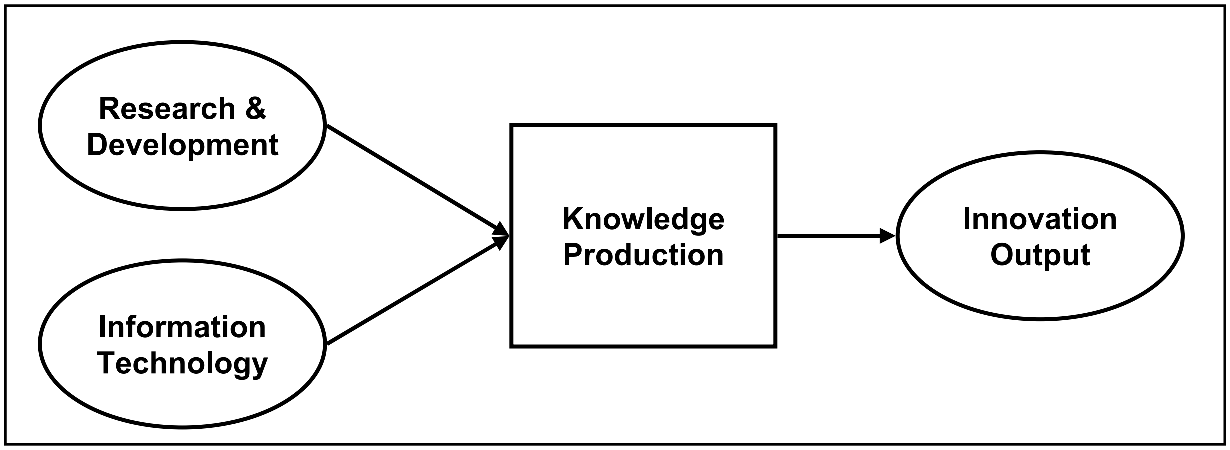

Figure 1: Augmented Knowledge Production Function

The output of a firm's knowledge production is new innovation (e.g., new products, services, processes, etc.), with patents being used as the primary, observable output indicator (Griliches 1990; Hall et al. 2005). Patents offer many attractive characteristics in this regard. First and foremost, the patent application examination process in the U.S. imparts a third-party, objective evaluation of an innovation, which must be novel, non-obvious, and useful i.e., having a useful purpose and operativeness (USPTO 2006). In addition, the USPTO standard has been relatively stable over time, making comparisons across years and industries more robust. Second, a patent provides a detailed record of the inventor, the industrial field into which the invention is classified, and citations of prior patents upon which it builds. The enforcement of the latter by patent examiners is especially important since it documents a recognition of "prior art", allowing the researcher to draw inferences based on the nature and quantity of cited patents.

Our research model can be expressed in Cobb-Douglas form:

$$P = \alpha RD^{\beta_1} IT^{\beta_2}, \tag{1}$$

where P is citation-weighted patent output, RD is R&D expense and IT is IT capital services (both in 1993 dollars). The statistical model we estimate for firm i at time t can be expressed as:

$$P_{it} = \alpha RD_{it}^{\beta_1} IT_{it}^{\beta_2} \varepsilon_{it} , \tag{2}$$

where ε_{it} is a multiplicative stochastic error term. For estimation, we transform the model into log-linear form and include controls Z_{it}:

$$\ln P_{it} = \alpha + \beta_1 \ln RD_{it} + \beta_2 \ln IT_{it} + \gamma Z_{it} + \varepsilon_{it} . \tag{3}$$

We control for firm size, time, and industry. All three have been identified as necessary controls in previous IT and R&D value research (Brynjolfsson and Hitt 2003; Bresnahan et al. 2002; Griliches 1990). Firm size is represented by log of firm sales in 1993 dollars. Time is represented through the use of year indicator variables. Industry controls are created through the use of Standard Industrial Classification (SIC) codes. Based on earlier research, we utilize a 1.5-digit SIC scheme which aggregates a number of 2-digit SIC industries into a more cohesive and stable 10-industry structure (Bresnahan et al. 2002; Brynjolfsson and Hitt 2003). Due to the limitations of our sample, only four of these industry groups remain in our analysis: durable, non-durable, process, and high technology manufacturing.

3.1. Data

The estimation of our model utilizes data from three principal sources. First, we use patents as the observable measure of knowledge production output. When considering such a measure, we could utilize raw patent counts as in several existing studies (Pakes and Griliches 1984; Hall et al. 1986; Crépon et al. 1998, Han and Ravichandran 2006). However, the benefits of this type of measure are mitigated by their inability to distinguish the variability in patent quality (Hall et al. 2001). IT-related research supports the use of quality-based innovation output measures. In particular, Gao and Hitt (2005, pg. 10) consider trademark counts "more appropriate" than raw patent counts since the latter do not incorporate the notion of product variety and differentiation.

Recognizing the limitation of raw patent counts, Hall et al. (2001) develop a patent measure which incorporates a citation-weighting methodology to account for variations in the quality or value of firm innovation. This measure weights each patent by the number of citations received by subsequent patents, and then normalizes the citation frequency across certain dimensions. Citation-weighting has been used in research concerning the economic value of a firm's innovations (Trajtenberg 1990; Hall et al. 2005), and innovation productivity and its impact (e.g., Hall and Ziedonis 2001; Thompson and Fox-Kean 2005). We employ this method to create our dependent variable *P*.

The raw patent and citation elements of our dependent variable are obtained from the NBER Patent Citation Database (Hall et al. 2001), which contains nearly 3 million successful US patent applications made between 1975 and 1999, and their citations by subsequent patents. While this dataset contains many details about each patent, it unfortunately does not distinguish between product and process innovations. The NBER dataset contains one row for each patent received by each firm. A separate table contains one row for each citation a patent had received up to the end of 1999. We join these tables to obtain a count of citations for each patent and update the citation count information to 2004 using USPTO data. These patent data are then linked to the Compustat database of publicly-traded US firms.[3]

Following the Hall et al. (2001) methodology, we then correct for two underlying factors in our output measure: trends (i.e., inflation) in citation-accretion across both time and field,[4] and the truncation of accumulated citations for a given patent vintage. Inflation may be addressed by using a fixed-effects benchmarking method to normalize the citations, purging them of year, field, and year-field effects. However, as it is desirable to allow variation among fields, the result is adjusted by dividing the number of citations received by a given patent and by the corresponding year-field mean (Hall et al. 2001, pg.30). This converts the output data from a count to a continuous-based measure. The truncation effect is addressed by augmenting the NBER data with citation count data from the USPTO to 2004. Hall et al. (2001) suggest that a three-year safety lag is prudent to allow for citation accretion, and that a two-year lag for patent application processing should be observed. Taking this into account, the more recent USPTO citation history allows us to use the patent data from 1997, but not from 1998 or 1999 as these

[3] The patents are matched to the Compustat universe of firms as of 1989. This has the effect of limiting our sample to those firms that belonged to the Fortune 1000 as of 1989.

[4] Hall et al. (2001) define field as the USPTO classification of technological categories, for which they provide a simplified taxonomy of six fields from more than 10,000 in the USPTO classification scheme.

years may not contain all of the patent applications that were eventually granted. Finally, we generate a new, alternate citation count based on the citations received within a fixed window of five years from the application date of each patent, and rescale these citations as described above. This removes the vintage effect of older patents for which time has allowed extra patents to accrue. Taken together, these three measures provide a robust assessment of each patent's quality.

When using patents as the basis for an innovation output measure, one must consider whether patents reflect the final innovation output of a firm. The granting of a patent does not guarantee a commercially successful innovation, given the extraordinarily complex task of integrating inventions and existing components into products valued by the marketplace (Fleming and Sorenson 2003). In addition, some inventions may not meet patentability requirements, while in other cases, firms may choose alternate methods of collecting economic rents from the invention.[5] This may be reflected in a low patents-to-R&D ratio in some firms. Despite these possibilities, recent evidence from innovation survey data shows broad agreement between the propensity of firms to apply for patents in relation to their innovation activities (Mairesse and Mohnen 2004; Ramirez and Kleis 2010). In addition, research indicates that such phenomena, when they do occur, tend to be industry-specific (Hall et al. 2001; Baily and Chakrabarti 1988). To control for some of this environmental patent variation, we include industry and year fixed effects in our econometric analysis.

We obtain data on information technology investment from the Computer Intelligence Infocorp (CI) database, which details the value of installed IT capital stock at approximately 800 of the Fortune 1000 firms annually, between 1987 and 1998. To create the database, CI collected data annually on the quantity of IT hardware in firms (e.g., mainframe, peripherals, mini-computer, PC systems, etc) using surveys, site visits, physical audits, and telephone interviews. The hardware counts, collected at the site and establishment level, were aggregated to the firm level by CI and a value of a firm's total IT stock was calculated based upon CI's estimate of hardware asset market value.

[5] As Scotchmer (2004) points out, patents are but one way to protect intellectual property, and they come with the significant trade-off of full disclosure. A firm may decide to use other methods, such as speed-to-market or trade secrets, depending upon the patenting environment, industry competitiveness and firm strategy.

Because of its detail, the CI data have been used widely in IT business value research (Brynjolfsson et al. 2002; Melville et al. 2007). However, due to a definition change in 1995, we follow the methodology of Chwelos et al. (2010) wherein hedonic methods are used to create an IT stock measure that is consistent across the entire 1987-1998 time frame.[6] We then create a measure of annual capital services flowing from the IT stock in constant quality-adjusted dollars. These IT measures represent the flow of services from (equivalently, payments to) IT assets that are used but not consumed in the production process (Jorgenson and Griliches 1967). Payments to employees are traditionally measured in a similar manner as are R&D expenses. The use of IT capital service variables allows for analysis using both R&D and IT flow variables. Finally, the use of IT capital service measures also accounts for measurement errors that are introduced by stock-based measures (Chwelos et al. 2010).

The yearly value of IT capital services is calculated using the rental price approach used by the Bureau of Labor Statistics. Rental prices reflect the user cost of capital and are defined as the sum of the rate of return, depreciation and expected rate of asset price change, net of income and property taxes. Rental prices were created for 12 SIC industries for two classes of IT assets, reflecting both decentralized (PCs) and centralized computing (Central Processing Equipment - CPE). Capital services estimates for a firm are then calculated by multiplying the IT capital stock of a firm by the appropriate rental price given the type of IT capital (PC or CPE) and industry of the firm.

Finally, from the Compustat database, we add a measure of research and development to our dataset. R&D activities are recorded annually as R&D expense and are reported in company financial statements. Accounting rules allow firms to expense research, defined as the "planned search or critical investigation aimed at discovery of new knowledge" which is specifically directed at a new or improved output (Oliver 2003, pg. 46). Development is defined as transforming "research findings or other

[6] Hedonic methods are used to determine the prices of IT components during the 1987-1994 time frame (prior to the definition change in 1995). These prices are applied across the entire 1987-1998 time frame and the resulting technology values are grouped into decentralized and centralized computing categories. These values are then adjusted through the application of hardware-specific price indexes. The adjustment takes into account not only price changes in similar technology over time, it also controls for quality change in these technologies. Analysis indicates that in both the pre- and post-1994 periods, these adjusted values are highly correlated with the original.

knowledge into a plan or design," which can include prototyping and building and operating pilot plants. Declared R&D expense also accounts for in-process research assets and intangibles purchased from other companies. Thus, the R&D expense measures in our dataset include both capital and labor spending put into use by firms to create new product, service, or process innovations. These measures have widely been used as an operationalized representation of the economic inputs to innovation (Pakes and Griliches 1984, Griliches 1981, Hall et al. 1986, Hall and Mairesse 1995, Han and Ravichandran 2006).

Since a firm's knowledge accumulates (and depreciates) over time, Pakes and Griliches (1984) include lagged R&D spending as part of their model's input. However, subsequent research on the lag structure shows a lack of influence of past R&D spending on future patent output (Hall et al. 1986). Since the impact of R&D on increments to the firm's knowledge stock is almost entirely contemporaneous, current R&D expenditure sufficiently captures the input magnitude.

The merged dataset generated from matching the patent, IT, and R&D data sources consists of 260 Fortune 1000 manufacturing firms with an initial total of 1,937 observations between 1987 and 1997. As firms choose to apply for patents relatively early in the R&D cycle (Griliches 1990), patent application year is matched to the year in which the R&D expense is recorded. In order to exclude firms with anomalous patent production (perhaps through acquisition of firms with in-process R&D), we further restrict our sample to firms that registered patents in at least 4 years between 1987 and 1997, leaving us with a final count of 201 firms for a total of 1,829 observations. Over the 11 year period, the median firm in the sample has \$2.6 billion in an annual sales, \$62.7 million in annual R&D expense, and \$9.6 million in annual IT capital services (Table 1).[7] The sample includes 162,381 patents, with the median firm

[7] All yearly financial data are indexed to 1993. Sales and R&D data are deflated using industry specific GDP price indexes from the Bureau of Economic Analysis (BEA). IT data are deflated using the PC price index from Berndt and Rappaport (2001) and the BEA price index for computers and peripheral equipment for all other classes of IT (i.e., mainframes, minicomputers, networking equipment, and computer peripherals) following Chewlos et al. (2010).

obtaining 24 successful patent applications per year. A total of 1,777,276 citations were recorded through the end of 2004, with the median firm receiving 208 citations on its patents in a given year.[8]

The panel is unbalanced, although over half the firms report patents in all 11 years and almost two-thirds of the firms have at least 10 observations. We restrict our sample to the Fortune 1000 manufacturing sector as the number of firms in the service sector that engage in significant R&D and patenting was small. Over the entire sample, each of the major service sectors (e.g., financial, transportation, etc.) was represented by only four or fewer firms. Finally, as shown in Table 2, the manufacturing firms in our sample are categorized into four industries.

4. Empirical Analysis

We conduct two sets of analyses. The first involves a thorough examination of our core research questions. We begin with our base Cobb-Douglas specification then conduct additional analyses to ensure robustness to issues such as unobserved variables, endogeneity, and choice of controls. The second involves further analysis of the impact of information technology on innovation output. This includes an examination of unique time periods including the mid to late 1990s, returns to IT capital in IT-using versus IT-producing industries, and the contribution of IT to highly-valued, blockbuster innovations.

4.1. Core Analysis

Our initial approach to estimating the Knowledge Production Function is ordinary least-squares (OLS) regression, using the Cobb-Douglas specification given in (3) and including controls for firm size (log of sales), industry (1.5-digit SIC scheme) and year. Because our dataset contains repeated observations of the same firm, we cannot assume independence of errors within firms. To address this, we perform the OLS estimation with the error clustered within firms. The clustered errors approach also includes the Huber-White adjustment to control for arbitrary forms of heteroskedasticity. The results of our base regression model are found in column 1 of Table 3. The estimates provide evidence of the relationship between R&D and IT on citation-weighted patent output. Both inputs have a positive and

[8] Our summary statistics use medians rather than averages because the patent and citation data is heavily skewed, as we discuss in section 4.2.

statistically significant effect (p<0.10), but the effect of R&D is approximately five times as large. The effect of sales (firm size control) is negative, which is consistent with the earlier finding that large firms are not as effective as small firms at producing patents per dollar of R&D (Griliches 1990). All of the year and industry controls are statistically significant which supports the expected impact of the competitive environment over time upon the KPF.[9] The model has an R-squared of 61%, indicating a substantial portion of the variation in patent output is explained by the independent variables.

In order to determine if the relative contributions of the inputs to the KPF changed over the course of our sample frame, we divide the sample into two periods (1987-1992 and 1993-1997) and estimate the model for each period. These results (Table 3, columns 2-3) show that while the estimated R&D coefficient remains remarkably stable, the IT coefficient is not statistically significant in the first six years of the sample. In contrast to the estimate for the overall sample, the IT coefficient for the latter five years is larger and significant at the 5% level. We will address this finding in more detail in section 4.2.

To relax the assumptions of the Cobb Douglas form, we extend our base analysis and estimate a translog specification of the KPF. The model to be estimated in logs is:

$$\ln P_{it} = \alpha + \beta_1 \ln RD_{it} + \beta_2 \ln IT_{it} + \beta_3 \ln RD_{it}^2 + \beta_4 \ln IT_{it}^2 + \beta_5 \ln RD_{it} IT_{it} + \gamma Z_{it} + \varepsilon_{it} \quad . \tag{4}$$

The estimation results are shown in column 4 of Table 3. The calculated partial elasticity estimates of R&D and IT ($\eta_{R\&D}$ and η_{IT}) are shown in Table 3 below the coefficient estimates. The partial elasticities of R&D and IT are similar to the OLS elasticity estimates for the entire sample and the 1987-1992 and 1993-1997 periods (columns 5-6). Since the coefficient estimate for the R&D-IT interaction term is not significant, we cannot infer that R&D and IT capital combine in some synergistic way to produce nonlinear increases in patent output.

Because the panel structure of the data violates the OLS assumption of independence of observations, OLS estimates can be inefficient. In addition, because there is added potential for firm-specific omitted variables to persist through time, the problem of omitted variable bias must be addressed.

[9] More granular industry controls, such as 2- and 3-digit SIC schemes, also produce significant control estimates.

Typically, a fixed effects or random effects panel estimator is used to model firm-level time-invariant unobserved variables.[10] We use the Hausman test to compare the estimates from fixed effects and random effects variations of our model and find we cannot conclusively reject the null hypothesis, indicating qualified support for a random effects approach.

We evaluate several random effects estimators[11] but find them prone to computational difficulties and unstable estimates of coefficients and standard errors. The basic random effects estimator requires strong assumptions of exogeneity and a firm-specific error term that is uncorrelated with observables. We find this estimator fails to produce statistically significant estimates of our principal variables. A more general approach, using the population-averaged random effects estimator, allows for the correlations within a firm to vary over time. A potential disadvantage of this approach is that it can run out of degrees of freedom over longer panels, which is what we encounter. Because of this limitation, we are only able to calculate estimates for subsamples of the first six and latter five years (Table 3, columns 7-8). The results show positive and significant coefficient estimates for R&D in both periods, and for IT in the latter period, which echoes the OLS estimates (albeit at a lower magnitude). In light of these difficulties, we propose that the clustered standard errors approach is in the spirit of random effects estimators, in that it allows the error component to contain omitted variables that are orthogonal to the model variables but common within the firm. Since the results from the population-averaged random effects estimator are qualitatively similar to the clustered OLS results, we proceed under the assumption that the latter estimates establish the upper bound of the output elasticities of our model variables. Our secondary analysis will also provide evidence that unobserved variables are not driving the results of our estimations.

These results consistently demonstrate a positive relationship between both IT and R&D with quality-adjusted patent production. However, we need to account for the possibility of endogenous factors

[10] The firm-level fixed effects (FFE) model is relatively common in IT value research, as in Brynjolfsson and Hitt (1995), who found FFE explained a sizeable amount of the output elasticity of IT. We found this approach resulted in non-significant coefficient estimates when applied to our context.

[11] We thank the Senior Editor and Associate Editor for their helpful suggestions in this regard.

that may influence the relationship between the independent variables and the dependent variable. While it is intuitive to think of R&D as an input to the production of patents, the opposite may also be true since the development and commercialization of a patented invention requires additional resources that will be reflected in the firm's reported R&D expense. In addition, innovations may stimulate further spending on the firm's IT infrastructure or projects related to marketing or implementing the innovation. This reciprocal relationship may cause the independent variables to be correlated with the model error term, which may lead to inconsistent OLS estimates.

To address these issues, we propose a set of instrumental variables to test for endogeneity and to estimate the model using two-stage least-squares (2SLS). The criteria for a good instrument are a high correlation with the endogenous independent variable but no correlation with the error term.[12] For R&D, we use competitors' R&D spending,[13] the Bureau of Labor Statistics wage index for white-collar non-sales occupations, and the firm's own one period lagged R&D. For IT, we use competitors' IT[14] and the firm's own one-period lagged IT capital services. Lagged R&D has been identified in earlier research as a useful instrument (Blundell et al. 1999). The wage index influences R&D spending but not patent output. Competitors' spending is expected to influence the firm's R&D and IT investments as industry factors, such as technical change (Allred and Swan 2005) and IT-driven competitive strategies (Sambamurthy et al. 2003), are known to influence a firm's investment decisions.

We also validate our instrumental variables using statistical tests. The Hansen's J statistic for our main model (Table 3, column 6) tests for overidentification of all the instruments. Under the joint null hypothesis, the instruments are uncorrelated with the error term and the exclusion restrictions are correct. Using the Stata command "ivreg2" (Baum et al. 2007), the test statistic is J=0.469 (p=0.791), so we fail to reject the null hypothesis. Further, we test the orthogonality conditions of the instruments using competitors' R&D and IT. The C statistic (ibid.) tests for exogeneity of a selected instrument by

[12] The correlations between R&D and the instruments are as follows: competitors' R&D=0.514; BLS wage index=0.093; own lagged R&D=0.990. The correlations between IT capital and the instruments are: competitors' IT=0.148; own lagged IT capital services=0.986.

[13] Competitors are defined as all firms reporting R&D within the same 4-digit SIC code in the Compustat database.

[14] Competitors are defined as all firms within the same 4-digit SIC code in the CI database.

comparing the Sargan-Hansen statistics of the model with and without the instrument. The computed *C* statistics are *C*=0.282 (*p*=0.596) and *C*=0.113 (*p*=0.737) respectively. Thus, we fail to reject the null hypothesis that both models are valid.

Having selected the instrumental variables, the Durbin-Wu-Hausman test (Davidson and Mackinnon 1993, p.237) can offer evidence of the presence of endogeneity. We conduct the test separately for R&D and IT. In both cases, we reject the null hypothesis that the OLS estimates are consistent. The results of the 2SLS estimation (again using the clustered standard error method), shown in Table 4, are comparable to the OLS estimates.[15] This offers some reassurance that endogeneity is not a major concern.[16] We find both IT and R&D have positive and significant coefficients over the full sample and in the latter half of the sample frame. In the 1987-1992 period, however, the estimated contribution of IT is not significant.

In addition to our measures to address endogeneity, we test our results for robustness against a number of alternative influences, based upon past findings in IT value and KPF research. These are: lag effects of IT upon innovation; our method of adjusting patent output for quality; the coarseness of our industry controls; and our adjustments for citation-truncation. These results are available in an online appendix.

4.2. Supplementary Analysis

We now explore several aspects of IT value analysis identified in prior literature that add depth to our examination of the IT-innovation relationship.[17] First, we test whether the role of IT evolved in support of innovation over the course of our sample period. Research examining economic growth in the 1990s identified an acceleration in labor productivity and total factor productivity since the mid 1990s. An increase in the rate of decline in technology prices and the deployment of IT in substitution for other

[15] The number of observations in this analysis is slightly lower due to cases that were dropped when firms did not have consecutive years of data for lagged independent and patent output variables.

[16] We acknowledge that using lagged variables as instruments without controlling for firm-level unobservables is not ideal, since the instruments may reflect the same endogeneity as the independent variables. Our analysis shows that, in this case, much of the explanatory power of the 2SLS estimation comes from the inclusion of lagged variables. Consequently, we must use caution when interpreting these results.

[17] We thank the associate editor and reviewers for these insightful suggestions.

more expensive firm inputs are highlighted as a key contributor to the resurgence in growth (Jorgenson 2001). It is possible that research and development is a firm activity that presents opportunities for further deepening in IT investment. Beyond investment motivated by price declines, quality improvements in IT could lead to new IT capabilities that complement other firm inputs (Chwelos et al., 2010), including those used in innovation production.

Adding to this line of research, we examine the contribution of information technology to innovation over the mid to late 1990s. As IT has been highlighted as a source of economic growth throughout the 1990s (Jorgenson 2001) and given the time frame of our dataset, we estimate and compare the contribution of IT to innovation between the 1987 to 1992 and 1993 to 1997 time periods.

Accordingly, we perform all of our estimations on both time periods (Table 3, columns 2-3, 5-8). This analysis highlights the stability of the positive and significant R&D elasticity estimate over the two periods. On the other hand, we find all estimates show IT elasticity to be larger and stronger in significance in the latter time period when compared with the former. This result is consistent with earlier research showing investments in information technology provided a higher level of impact during the mid to late 1990s versus its return during the start of the decade (Chwelos et al., 2010; Stiroh 2002; Gordon 2000).

Our second supplementary analysis seeks to compare our findings to prior research that examined the contribution of technology to the U.S. economic revival in the 1990s—in particular, whether IT-producing or IT-using industries were the source of U.S. productivity growth. The results of these analyses are mixed, with some research highlighting IT-producing industries as the main contributors to economic growth (Gordon 2000), while other research identifies both IT-producing and IT-using industries as contributing to the productivity rivalry (Stiroh 2002; Jorgenson 2001).

We expand our analysis to examine the relationship between information technology and innovation within these two industry categories. If they did have differential impacts on U.S. productivity growth, is this reflected in the IT-innovation relationship? To test this possibility, we divide our sample according to the 3-digit SIC codes associated with information and communication technology manufacturing. The division resulted in 1,311 IT-using firm observations and 254 IT-producing firm observations. Compared with the entire sample (Table 5, column 1), the results for IT-using firms (column 2) are similar, suggesting that firms of this type are benefiting from IT used in the creation of product and process innovations. On the other hand, in IT-producing firms (column 3), the estimated IT elasticity is not significant, while the estimated R&D elasticity is noticeably larger (1.255% at $p<0.001$) than that for all firms and for IT-using firms.

There are several possible explanations for the results involving IT-producing firms. First, some IT producers like Cisco Systems pursue a model of innovation through acquisition. Rather than investing in R&D and related IT like traditional industrial-era firms, these IT-producing firms identify and acquire new innovations outside their organizational boundary. Effectively, traditional innovation investment shifts from the R&D function to the mergers & acquisitions function in some IT producers. As a result, the amount of R&D expensed may be lower, while the contribution of R&D to patent output becomes larger, relative to their IT capital. An alternative interpretation is that the creation of innovation-intensive IT products are more dependent upon the firm's stock of intangible knowledge rather than the application of tangible information technology assets. Unfortunately, the low number of observations for the IT-producing subsample (some 20 per year) demands that we exercise caution when interpreting these results.

Our third supplementary analysis concerns the contribution of IT to breakthrough or radical innovations. While rare, such "blockbuster" innovations can create superior value by unleashing market-changing forces. Indeed, some innovation-focused firms such as those in the pharmaceutical industry design their business models around the pursuit of these unique creations (Gilbert et al. 2003). Research has identified the number of citations a patent receives as an indicator of the value of an innovation, with blockbuster patents accruing far more citations than the average patent (Owens-Smith and Powell 2003; Hall et al. 2001). The link between IT and blockbuster innovation has not been examined in the IT literature prior to this study. However, university-level research has identified *knowledge flows* and *access to information for external partners* as key factors related to the creation of high-impact patents

(Owen-Smith and Powell 2003). We expect that information technology enables these factors in the firm's pursuit of blockbuster innovations, and that this relationship will be reflected in our data.

The distribution of patents by citation frequency exhibits a very long tail (Figure 2), with the median falling at 6.4 citations amid a range from 0 to over 400 among the more than 162,000 patents in our data. By restricting the sample for each firm-year to only those patents with citation counts in a certain quartile, or above a certain percentile threshold, we may estimate the associated output elasticity of IT and R&D expenditure with innovations ranging from incremental to radical. The results from these restricted samples are reported in Table 6.

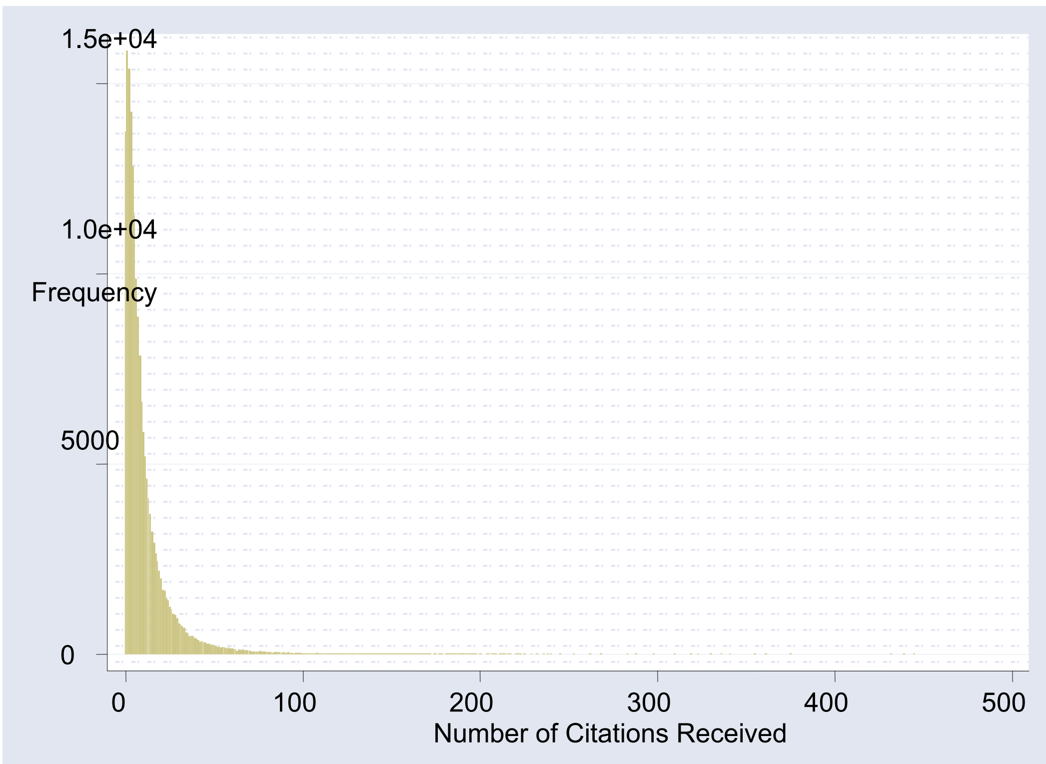

Figure 2: Histogram of Citations Received by Individual Patents

By comparing the estimated output elasticities across the columns, it is evident that the contribution of additional IT capital is greatest for patents in the lowest (1st and 2nd) quartiles of citation frequency, but declines when applied to more frequently-cited patents. The results suggest that the contribution of IT capital to "blockbuster" patents (in the 90th or greater percentile) is not statistically significant. Research and development, on the other hand, has a higher output elasticity estimate for the quartiles that include more frequently-cited patents.

These results imply that the effect of general, firm-wide investment in IT is more likely to facilitate incremental innovation. It appears IT-enabled improvements in the innovation process, such as data capture, sharing, analysis, test, etc., are more applicable to building upon current knowledge. In contrast, the contribution of R&D to the production of more innovative patents may highlight the non-technical nature of the radical creative process. It is possible that data related to such blockbuster ideas are not available in a form than can be captured and analyzed using IT. Rather, such raw and innovative data exist in a non-expressive form only available to the minds of research and development personnel. Such knowledge does not become available until the newly developed idea has advanced enough to be translated into a tangible, binary form. Such radically new concepts are so novel and unique that they can only be produced with inputs other than information technology.

Overall, our estimates of the innovation elasticity of IT and R&D are stable within the range of 0.14-0.28 and 0.65-0.90, respectively, and appear robust to different specifications and methods. Further, we show that the contribution of IT to innovation is more evident in specific firms, periods and innovation quality strata. Taken together, these findings reduce the likelihood that unobserved variables are driving the relationship between IT and innovation output. While an unknown cause of firm-level heterogeneity could influence our results, such a factor(s) would have to apply only to incremental innovation, IT-using firms and the 1993-1997 period.

The positive and significant output elasticity identified for IT, across multiple assumptions and specifications, presents strong evidence of the critical role of IT in innovative activity. The magnitude of IT elasticity is smaller than that for R&D elasticity, however, at a high level, this is not surprising given the central role of intangible capital (e.g., scientist knowledge, skill, creativity, etc.) in innovation. While it is possible that the point estimate of IT elasticity could be higher and more accurate with the inclusion of other IT spending dimensions (software, labor, etc.), were such data available, we would expect its relative magnitude to remain smaller than that of R&D.

5. Discussion

The contribution of IT to firm-level productivity has been demonstrated in prior research, yet much remains unknown about the mechanisms by which this is accomplished. The production of intangible organizational outputs, such as knowledge, is a key area in which to look for IT's contribution to a firm's operations and, ultimately, its value. In an effort to uncover IT's contribution to the creation of new knowledge, we augment the Knowledge Production Function (Pakes and Griliches 1984) to include IT capital input, a variable previously excluded in innovation research. To examine the relationships between IT, innovation activity, and innovation output, we analyze a unique dataset containing annual data on R&D expenditures, IT capital flows, and patent citations for 201 Fortune 1000 firms for the years 1987 to 1997.

Our estimates indicate that IT and R&D both play a positive and significant role in innovation production. In our panel of large manufacturing firms, a 1% increase in IT capital services is associated with an increase in (citation-weighted) patent output of 0.166% in the 1987-1997 period. Further, we find evidence that the role of IT in innovation became stronger in the last five years of our sample, as firms increased their IT investments dramatically. Beyond capital deepening, the contribution of IT during this time frame is also due, in part, to the new IT capabilities being introduced at the time, namely networking and internet-based interconnectivity. Indeed, research at the economy level lends credence to this supposition (Jorgenson 2001, Stiroh 2002).

Our estimates of the augmented KPF are consistent with earlier research in two key respects: R&D has a positive impact on citation-weighted patent output, while firm size is inversely related to patent output. Indeed, the impact on patent output of a 1% increase in R&D is 0.896%, about five times larger than that of IT. This larger magnitude is expected, since R&D spending is a direct input to innovation process, while firm-wide IT investment will support the firm's productive and administrative processes in addition to supporting the innovation creation process. The firm size effect is also confirmed to the extent that our OLS and 2SLS estimates of the control variable (sales) are negative (with the exception of the patents with first-quartile citation frequencies).

Our results also demonstrate an important aspect of IT and the innovation creation process: although firms invest specifically in R&D inputs, including dedicated IT spending within R&D programs, the impact of IT on innovation goes beyond R&D-specific IT spending. Specifically, our results suggest that general infrastructure and enterprise technologies of a firm (networks, email, telephony, accounting and finance ERP modules, etc.) also contribute to the innovation process. Interestingly, we also find that the effect of IT on innovation was strongest for "incremental" patents and non-significant for "blockbuster" patents. This suggests that while IT contributes broadly and significantly to innovation, whether measured by patents or citations, IT alone does not lead to breakthrough innovations. Rather, breakthrough or radical innovations may be more dependent on other factors, such as the tacit knowledge of R&D scientists and engineers.

Finally, we contextualize our results in terms of market value impact. Using a sample of 4,864 publicly-traded US firms over the 1979-1998 time period, Hall et al. (2005) found that if the average number of citations received by a firm's patents increases by one, the market value of the firm increases by 3%. Assuming this result is generalizable to our sample, we can estimate the marginal impact of IT investment on innovation output and extrapolate to obtain the expected increase in market value. Using our upper- and lower-bound IT elasticities for the 1993-1997 period, we estimate the median firm in our sample would need to increase its IT capital flows by 39-81% ($3.8-7.7 million) in order to obtain one additional citation for each of its patents. While this amount is at first glance rather large, we note that between 1993 and 1997 the median firm increased its IT capital services by 26% ($2.5 million). Furthermore, the innovation-driven 3% market value increase predicted by Hall et al. would amount to $41 million for the median firm in our sample. Thus, our estimates of the return to investment for IT-driven innovation appear to be economically meaningful.

While our results confirm many of our expectations, we recognize several limitations of our work. First, our dataset is not without its shortfalls; the Compustat R&D data cannot be broken down into spending by the type of innovation pursued (e.g., product or process). Doing this would allow for a refined analysis to identify the types of innovation efforts that are more likely to pay off in a finished and highly-valued innovation. The R&D measure also does not encompass any spending information on informal innovation activity that may be conducted in firms. However, given explicit FASB rules and definitions, annual R&D expenditures must be reported, thereby constraining off-the-book innovation spending.

While our information technology construct incorporates all types of IT elements including hardware, software, IT skill, and organizational complements, the CI measures are based exclusively on IT hardware. For example, product innovation may require investments in both IT as well as new marketing skills as a firm moves into new marketplaces or new production processes to manufacture new products (Garcia and Calantone 2002). This data shortfall limits the identification of exact point estimates of IT's impact on innovation output. However, insofar as investments in IT hardware are associated with these other factors, our IT measures provide reasonable insight into the IT construct.

The CI data also cannot be broken down to into measures of IT that directly support R&D and those that do not. While the availability of more focused measures of R&D-related IT spending[18] would provide a more comprehensive and precise estimate of IT's impact on innovation, such data are prohibitively difficult to obtain. However, our dataset is not without its merits in relation to innovation activity analysis. The CI data represent a comprehensive, firm-level measure of information technologies primarily devoted to infrastructure. Such technologies (e.g., networking technologies, email applications, databases, etc.) have been explicitly mentioned as enabling collaboration and R&D (Kumar and van Diesel 1996; Rice 1994). As a result, the CI data, while not ideal, offer insight into IT's contribution to firm innovation.

Patents are a good proxy for measuring the output of firm innovation efforts, however, they represent only one type of outcome associated with innovation and are not guaranteed at that. In addition,

[18] R&D-related IT spending measures would provide a more direct match to our IT construct. The ideal measure would include the percentage cost of enterprise infrastructure technologies that supports R&D (networks, email, etc.) as well as incremental IT investments made specifically for R&D projects. Project specific R&D-related IT could include specialized technologies such as CAD/CAM systems used in new product design, data analysis applications like specialized statistical programs for market research, and the customization of software for the creation of innovative process specific activities (e.g., a new transaction process like Amazon's 1-click).

as Griliches (1990) summarized, “not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in … the magnitude of inventive output associated with them.” Hence, although our data represent patented innovations, with adjustments to reflect their quality, we recognize that they do not represent all incremental innovations of a firm.

Beyond facing the aforementioned data challenges, in the spirit of the KPF literature stream (Pakes and Griliches 1984, Crépon et al. 1998), future research could jointly estimate production and patent functions. In this way, one could examine both the direct effects of IT on firm performance while accounting for the indirect effects of IT that take place through new innovations. Market value performance would be a natural first area for examination as a rich, independent literature streams exists in both the IT and R&D areas (see Melville et al. 2001 and Hall 2000 for literature surveys).

Future research could also draw on the natural link between innovation and location-specific effects. While innovation research has long acknowledged the importance of proximity to other innovators and the nature of a firm’s external business environment, these factors are a relatively new area of inquiry for IT business value research. In the context of the internet era, as well as the shift of some IT knowledge-work overseas, it is possible that today’s IT is reshaping the notion of what is “location-specific” as applied to innovation.

6. Conclusion

Empirical researchers have accumulated significant evidence of IT’s contribution to firm-level productivity. However, the underlying mechanisms by which this effect occurs are not well understood. By examining intangible outputs, such as innovation, we shed new light on the use of IT to create firm value. In particular, we identify IT as a new and effective input to the R&D-driven innovation process. Finally, by using patent citations as a measure of quality-adjusted innovation output, we overcome a major limitation of innovation measurement associated with the Knowledge Production Function. By doing so, we help set the stage for greater understanding of the value of innovation and IT in the overall production context.

References:

Acs, Z., D. Audretsch. 1989. Patents as a Measure of Innovative Activity. *Kyklos* **42** 171-180.

Agarwal, R., B.L. Bayus. 2002. The Market Evolution and Sales Takeoff of Product Innovations. *Management Science* **48**(8) 1024-1041.

Agrawal, A., A. Goldfarb. 2008. Restructuring Research: Communication Costs and the Democratization of University Innovation. *American Economic Review* **98**(4) 1578-1590.

Allred, B. and K.S. Swan. 2005. The Mediating Role of Innovation on the Influence of Industry Structure and National Context on Firm Performance. *Journal of International Management* **11** 229– 252.

Ba, S., P. Pavlou. 2002. Evidence of the Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior. *MIS Quarterly* **26**(3) 243-268.

Baily, M.N., A.K. Chakrabarti. 1988. *Innovation and the Productivity Crisis*. The Brookings Institution, Washington, D.C.

Balachandra, R., J. Friar. 1997. Factors for Success in R&D Projects and New Product Innovation: A Contextual Framework. *IEEE Transactions on Engineering Management* **44**(3) 276-287.

Baum, C.F., Schaffer, M.E., Stillman, S. 2007. ivreg2: Stata Module for Extended Instrumental Variables/2SLS, GMM and AC/HAC, LIML and K-Class Regression. Retrieved from: http://ideas.repec.org/c/boc/bocode/s425401.htmal, February 2009.

Bartholomew, D. 2005. Manufacturers Nibbling on PLM. *Industry Week* **254** (4) 63.

Berndt, E.R., N.J. Rappaport. 2001. Price and Quality History of Desktop and Mobile Computers: A Quarter-Century Historical Overview. *The American Economic Review* **91**(2) 268-273.

Blundell, R., R. Griffith, J. Van Reenen . 1999. Market Shares, Market Value and Innovation in a Panel of British Manufacturing Firms. *Review of Economic Studies* **66** 529-554.

Brennan, A., Dooley, L. 2005. Networked creativity: a structured management framework for stimulating innovation. *Technovation* **25** 1388–1399.

Bresnahan, T., E. Brynjolfsson, L. Hitt. 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *The Quarterly Journal of Economics* **117**(1) 339-376.

Brockhoff, K. 1992. R&D Cooperation between Firms-A Perceived Transaction Cost Perspective. *Management Science* **38**(4) 514-524.

Brown, S.L., Eisenhardt, K.M. 1995. Product Development: Past Research, Present Findings, and Future Directions. *The Academy of Management Review* **20**(2) 343-378.

Brynjolfsson, E., L. Hitt. 1995. Information Technology as a Factor of Production: The Role of Differences Among Firms. *Economics of Innovation and New Technology* **3**(4) 183-200.

Brynjolfsson, E., L. Hitt. 2003. Computing Productivity: Firm-Level Evidence. *Review of Economics & Statistics* **85**(4) 793-808.

Brynjolfsson, E., L. Hitt, S.K. Yang. 2002. Intangible assets: Computers and organizational capital. *Brookings Papers on Economic Activity* 137-198.

Cassiman, B., R. Veugelers. 2006. In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science* **52**(1) 68-82.

Chan, T., J.A. Nickerson, H. Owan. 2007. Strategic Management of R&D Pipelines with Co-specialized Investments and Technology Markets. *Management Science* **53**(4) 667-682.

Christensen, J., M. Olesen, J. Kjaer. 2005. The Industrial Dynamics of Open Innovation—Evidence from the Transformation of Consumer Electronics. *Research Policy* **34**(10) 1533-1549.

Chwelos, P., R. Ramirez, K. Kraemer, N. Melville. 2010. Does Technological Progress Alter the Nature of Information Technology as a Production Input? New Evidence and New Results. *Information Systems Research* **21**(2).

Crépon, B., E. Duguet, J. Mairesse. 1998. Research, Innovation and Productivity: An Econometric Analysis at The Firm Level. *NBER Working Paper* 6696.

Davidson, R., J. G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. Oxford University Press, New York.

Dibrell, C., P. S. Davis, J. Craig. 2008. Fueling Innovation through Information Technology in SMEs. *Journal of Small Business Management* **46**(2) 203-218.

Dodgson, M., D. Gann, A. Salter. 2006. The Role of Technology in the Shift Towards Open Innovation: The Case of Procter & Gamble. *R&D Management* 36(3) 333-346.

Dougherty, D., C. Hardy. 1996. Sustained Product Innovation In Large, Mature Organizations: Overcoming Innovation-To-Organization Problems. *Academy of Management Journal* **39**(5) 1120-1153.

Drukker, D. M. 2003. Testing for Serial Correlation in Linear Panel-Data Models. *Stata Journal* **3**(2) 168-177.
Elliott, M. 2006. Integrating the Drug Discovery Laboratory. *Scientific Computing* May 16-18.
Enkel, E., O. Gassmann, H. Chesbrough. 2009. Open R&D and Open Innovation: Exploring the Phenomenon. *R&D Management* 39(4) 311-316.
Fleming, L., O. Sorenson. 2003. Navigating the Technology Landscape of Innovation. *Sloan Management Review* **44**(2) 15-23.
Gao, G., L.M. Hitt, L.M. 2005. IT and Product Variety: Evidence from Panel Data, in: Working Paper, Robert H. Smith School of Business, University of Maryland, College Park, MD.
Garcia, R., R. Calantone. 2002. A Critical Look at Technological Innovation Typology and Innovativeness Terminology: A Literature Review. *Journal of Product Innovation Management* **19** 110-132.
Gilbert, J., P. Henske, A. Singh. 2003. Rebuilding Big Pharma's Business Model. *In Vivo: The Business & Medicine Report* **21**(10).
Gordon, S., Tarafdar, M., Cook, R., Maksimoski, R., Rogowitz, B. 2008. Improving the Front End of Innovation with Information Technology, *Research Technology Management* **51**(3) 50-58.
Griliches, Z. 1981. Market Value, R&D, and Patents. *Economic Letters* **7** 183-187.
Griliches, Z., 1990. Patent statistics as economic indicators: A survey. *Journal of Economic Literature* **28** 1661-1707.
Hall, B. H. 2000. *Innovation and Market Value*. In R. Barrell, G. Mason, and M. O'Mahoney, eds., Productivity, Innovation and Economic Performance, Cambridge, England: Cambridge University Press.
Hall, B.H., Z. Griliches, J. A. Hausman. 1986. Patents and R&D: Is there a lag? *International Economics Review* **27**(2) 265-83.
Hall, B.H., A.B. Jaffe., M. Trajtenberg. 2001. The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools. *NBER working pape*r 8498.
Hall, B.H., A.B. Jaffe., M. Trajtenberg. 2005. Market Value and Patent Citations. RAND Journal of Economics **36**(1) 16-38.
Hall, B.H., J. Mairesse. 1995. Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics* **65** 263-293.
Hall, B.H., R. Ziedonis. 2001. The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979–1995. *RAND Journal of Economics* **32**(1) 101–128.
Hamermesh, D.S., S.M. Oster. 2002. Tools or Toys? The Impact of High Technology on Scholarly Productivity. *Economic Inquiry* **40**(4) 539-555.
Han S., T. Ravichandran. 2006. Does IT Impact Firm Innovativeness: An Empirical Examination of Complementary and Direct Effects. Proceedings Americas Conference on Information Systems (AMCIS).
Hatch, N.W., D.C. Mowery. 1998. Process Innovation and Learning by Doing in Semiconductor Manufacturing. *Management Science* **44**(11) 1461-1477.
Henderson, R., I.M. Cockburn. 1994. Measuring Competence? Exploring Firm Effects In Pharmaceutical Research. *Strategic Management Journal* **15** 63-84.
Horn, P.M. 2005. The Changing Nature of Innovation. *Research Technology Management* **48**(6) 28-33.
Istook, C. 2000. *Journal of Textile and Apparel Technology and Management* **1**(1).
Jorgenson, D. W. 2001. Information Technology and the U.S. Economy. *The American Economic Review* **91**(1) 1-32.
Jorgenson, D. W., Z. Griliches. 1967. The Explanation of Productivity Change. *The Review of Economic Studies* **34**(3) 249-283.
Kleis, L., Chwelos, P., Ramirez, R., and Kraemer, K. (2003). Information Technology and Innovation: The Impact of IT Investment on Intangible Outputs. Presented at the Workshop on Information Systems and Economics (WISE), December 7-8, 2003, Seattle, WA.
Konicki, S. (2002). Time trials. *InformationWeek* **891** 36.
Kortum, S., J. Lerner. 1998. Stronger Protection or Technological Revolution: What is Behind the Recent Surge in Patenting? *Carnegie-Rochester Conference Series on Public Policy* **48** 247-304.
Kremp, E., J. Mairesse. 2004. Knowledge Management, Innovation and Productivity: A Firm Level Exploration Based on French Manufacturing CIS3 Data. *NBER Working Paper* 10237.
Kumar, K., H.G. van Dissel. 1996. Sustainable Collaboration: Managing Conflict and Cooperation in Interorganizational Systems. *MIS Quarterly*, **20**(3), 279-300.
Lee, H., B. Choi. 2003. Knowledge Management Enablers, Processes, and Organizational Performance: An Integrative View and Empirical Examination. *Journal of Management Information Systems* **20(**1) 179-228.

Madsen, J. 2008. Semi-Endogenous Versus Schumpeterian Growth Models: Testing the Knowledge Production Function Using International Data. *Journal of Economic Growth* **13** 1–26.

Mairesse, J., P. Mohnen. 2004. The Importance of R&D for Innovation: A Reassessment Using French Survey Data. *NBER Working Paper* 10897.

Majchrzak, A., L.P. Cooper, O.E. Neece. 2004. Knowledge Reuse for Innovation. *Management Science*, **50**(2) 174-188.

Majchrzak, A, C.M. Beath, R.A Lim, W.W. Chin. 2005. Managing Client Dialogues During Information Systems Design to Facilitate Client Learning. *MIS Quarterly* **29**(4) 653-672.

Malhotra, A., A. Majchrzak, R. Carman, V, Lott. 2001. Radical Innovation without Collocation: A Case Study at Boeing-Rocketdyne. *MIS Quarterly* **25**(2) 229-249.

Mansfield, E.. 1984. Patents and Innovation: An Empirical Study, *Management Science* **32** 173-181.

Melville, N., V. Gurbaxani, K. Kraemer. 2007. The Productivity Impact of Information Technology Across Competitive Regimes: The Role of Industry Concentration and Dynamism. *Decision Support Systems* **43** 229–242.

Mithas, S., M.S. Krishnan, C. Fornell. 2005. Why Do Customer Relationship Management Applications Affect Customer Satisfaction? *Journal of Marketing* 69(4)201-209.

Mithas, S., M.S. Krishnan, C. Fornell. Information Technology and Customer Satisfaction 1994-2006: Theory and Evidence," in: Working Paper, Robert H. Smith School of Business (Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=901643), College Park, 2009.

Nambisan, S. 2003. Information Systems as a Reference Discipline for New Product Development. MIS Quarterly **27**(1) 1-18.

Narayanan, V., F. Douglas, D. Schirlin, G. Wess, D. Geising. 2004. Virtual Communities as an Organizational Mechanism for Embedding Knowledge in Drug Discovery: The Case of Chemical Biology Platform. *Journal of Business Chemistry* **1**(2) 37-47.

Narver, J., S. Slater, D. MacLachlan. 2004. Responsive and Proactive Market Orientation and New-Product Success. *Journal of Product Innovation Management* **21** 334–347.

Nellore, R., Balachandra. 2001. Factors Influencing Success in Integrated Product Development (IPD) Projects. *IEEE Transactions On Engineering Management* **48**(2) 164-174.

Nerkar, A., S. Paruchuri. 2005. Evolution of R&D Capabilities: The Role of Knowledge Networks Within a Firm. *Management Science* **51**(5) 771-785.

Oliver, J. R. 2003. Accounting and Tax Treatment of R&D: An Update. *The CPA Journal* **73**(7) 46-49.

Owen-Smith, J., W. Powell. 2003. The Expanding Role of University Patenting in the Life Sciences: Assessing the Importance of Experience and Connectivity. *Research Policy* **32** 1695-1711.

Pakes, A., Z. Griliches. 1984. Patents and R&D at the Firm Level: A First Look. Z. Griliches ed. *R&D, Patents, and Productivity*. University of Chicago Press, Chicago.

Paulraj, A., A. Lado, I. Chen. 2008. Inter-Organizational Communication as a Relational Competency: Antecedents and Performance Outcomes in Collaborative Buyer–Supplier Relationships. *Journal of Operations Management* **26**(1) 45-64.

Quinn, J. B., J. J. Baruch, K. A. Zien. 1997. *The Innovation Explosion : Using Intellect and Software to Revolutionize Growth Strategies*. Free Press, New York.

Ramirez, R.V., L. Kleis. 2010. *The Firm Innovation Process: How Critical is Information Technology?* Working Paper.

Rice, R. E. 1994. Relating Electronic Mail Use and Network Structure to R&D Work Networks and Performance. *Journal of Management Information Systems* **11**(1) 9-29.

Roberts, P.W. 1999. Product Innovation, Product–Market Competition And Persistent Profitability in the U.S. Pharmaceutical Industry. *Strategic Management Journal.* **20** 655–670.

Rothwell, R. 1994. Towards the Fifth Generation Innovation Process. *International Marketing Review* **11**(1) 7-31.

Ryssel, R., T. Ritter, H. Gemunden. 2004. The Impact of Information Technology Deployment on Trust, Commitment and Value Creation in Business Relationships. *Journal of Business & Industrial Marketing* **19**(3) 197 – 207.

Sambamurthy, V., A. Bharadwaj, V. Grover, 2003. Shaping Agility through Digital Options: Reconceptualizing the Role of Information Technology in Contemporary Firms. *MIS Quarterly* **27**(2) 237-263.

Sangiovanni-Vincentelli, A.L. 2003. Electronic-System Design in the Automobile Industry. *IEEE Micro*, **21**(3) 8-18.

Scotchmer, S. 2004. *Innovation and incentives*. MIT Press, Cambridge.

Schilling, M., C. Hill. 1998. Managing the New Product Development Process: Strategic Imperatives. *The Academy of Management Executive* **12**(3) 67-81.

Scott, J. 2000. Facilitating Interorganizational Learning with Information Technology. *Journal of Management Information Systems* **17**(2) 81 – 113.
Stiroh, K. 2002. Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say? *American Economic Review* **92**(5) 1559-1576.
Sudarsan, R., S.J. Fenves, R.D. Sriram, F. Wang, 2005. A Product Information Modeling Framework for Product Lifecycle Management, *Computer-Aided Design* **37**(13) 1399-1411.
Swink, M. 2006. Building Collaborative Innovation Capability. *Research Technology Management* **49**(2) 37-47.
Tanriverdi, H. 2005. Information Technology Relatedness, Knowledge Management Capability, and Performance of Multibusiness Firm. *Management Information System Quarterly* **29(**2) 311-324.

Teresko, J. 2004. P&G's secret: Innovating innovation. *Industry Week* **253**(12) 26.

Thomke, S.H. 2006. Capturing the Real Value of Innovation Tools. *MIT Sloan Management Review* **47**(2) 24-32.
Thompson, P., M. Fox-Kean. 2005. Patent Citations and the Geography of Knowledge Spillovers: A Reassessment. *American Economic Review* **95**(1) 450-460.
Trajtenberg, M. 1990. A Penny for Your Quotes: Patent Citations and The Value of Innovations. *Rand J. Econ.* **21**(1) 172-187.
USPTO (United States Patent and Trademark Office). 2006. General Information Concerning Patents. Retrieved September 2006, http://www.uspto.gov/web/offices/pac/doc/general/index.html#patent .
Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.
Zahay, D., A. Griffin, E. Fredericks. 2004. Sources, Uses, and Forms of Data in The New Product Development Process. *Industrial Marketing Management* **33**(7) 657-666.

Table 1: Descriptive Statistics

Variable	Obs	Median	Std. Dev.	Min	Max
Sales*	1,829	2,642.93	15,728.26	440.64	166,620.20
R&D expense*	1,829	62.76	784.87	0.46	8,359.77
IT capital services*	1,829	9.68	53.10	0.10	787.00
Patents	1,829	24.00	191.80	1.00	2,405.00
Patent Citations Received	1,829	208.00	2,423.85	1.00	31,733.00
Patent Citations Received (adjusted)	1,829	211.09	2,464.27	1.00	36,683.25
5-year capped Patent Citations Received	1,820	104.00	1,598.27	1.00	27,082.00
5-year capped Patent Citations Received (adjusted)	1,820	105.44	1,496.93	0.79	23,145.31

*(millions, 1993 dollars), 201 Fortune 1000 firms

Table 2: Sample Composition by Industry

Industry	Observations	Percent of observations	Firms	Percent of firms
Non-durable Manufacturing	112	6.1%	12	6.0%
Durable Manufacturing	571	31.0%	63	31.3%
Process Manufacturing	517	28.1%	57	28.4%
High-tech Manufacturing	639	34.7%	69	34.3%

Note: The industry classification is motivated by prior IT value research (Bresnahan et al. 2002) and derived from grouping 20 2-digit SIC firms into 10 categories. The firms in our sample represent only 4 of these 10 categories.

Table 3: Estimation Results

	1	2	3	4	5	6	7	8
	OLS (Cobb-Douglas) (clustered robust standard errors)			OLS (Translog) (clustered robust standard errors)			Random Effects Panel (population-averaged)	
	all years	1987-1992	1993-1997	all years	1987-1992	1993-1997	1987-1992	1993-1997
ln(R&D)	0.896***	0.893***	0.897***	0.885***	0.939***	0.814***	0.766***	0.658***
	(0.0701)	(0.0755)	(0.0860)	(0.0953)	(0.123)	(0.126)	(0.0683)	(0.0709)
ln(IT)	0.166*	0.0970	0.259**	0.267**	0.191	0.377**	0.0880	0.142*
	(0.0946)	(0.0947)	(0.128)	(0.126)	(0.213)	(0.167)	(0.0787)	(0.0755)
ln(Sales)	-0.229**	-0.202*	-0.254*	0.0536	0.0750	0.135	-0.0628	0.0310
	(0.104)	(0.103)	(0.133)	(0.0473)	(0.104)	(0.0905)	(0.0975)	(0.105)
ln(R&DxIT)				-0.0205	-0.0232	-0.0472		
				(0.0264)	(0.0460)	(0.0407)		
$\ln(R\&D)^2$				0.00254	-0.0131	-0.0775		
				(0.0311)	(0.0683)	(0.0736)		
$\ln(IT)^2$				-0.257**	-0.246**	-0.260*		
				(0.112)	(0.119)	(0.140)		
Constant	3.196*	4.598**	2.143	4.891*	5.412**	5.005	2.296	-0.936
	(1.933)	(1.867)	(2.391)	(2.482)	(2.701)	(3.069)	(1.646)	(1.868)
N	1829	1006	823	1831	1008	823	1006	823
R-squared	0.610	0.627	0.596	0.611	0.625	0.598	.	.
$\eta_{R\&D}$	0.896***	0.893***	0.897***	0.896***	0.890***	0.900***	0.766***	0.658***
	(0.0701)	(0.0755)	(0.0860)	0.069	0.078	0.085	(0.0683)	(0.0709)
η_{IT}	0.166*	0.0970	0.259**	0.177*	0.112	0.239*	0.0880	0.142*
	(0.0946)	(0.0947)	(0.128)	0.103	0.116	0.132	(0.0787)	(0.0755)

- Dependent variable: log of citation-weighted patents
- *** *p<0.01*, ** *p<0.05*, * *p<0.10*
- Estimates for Year and Industry indicators omitted from results

Table 4: 2SLS Estimation Results

	1 2SLS all years	2 2SLS 1987-1992	3 2SLS 1993-1997
ln(R&D)	0.896***	0.900***	0.889***
	(0.0769)	(0.0850)	(0.0911)
ln(IT)	0.198*	0.114	0.287*
	(0.111)	(0.111)	(0.150)
ln(Sales)	-0.263**	-0.234**	-0.286**
	(0.114)	(0.117)	(0.142)
Constant	3.472*	4.867**	2.458
	(1.995)	(2.041)	(2.421)
Observations	1565	788	777
R-squared	0.613	0.633	0.599

- Dependent variable: log of citation-weighted patents
- Cluster-adjusted robust standard errors
- *** *p<0.01,* ** *p<0.05,* * *p<0.10*
- Estimates for Year and Industry indicator variables omitted from results

Table 5: IT-producing vs. IT-using industries

	1 All firms	2 IT-using 3-digit SIC	3 IT- producing 3-digit SIC
ln(R&D)	0.896***	0.786***	1.255***
	(0.0769)	(0.0938)	(0.304)
ln(IT)	0.198*	0.211*	0.0683
	(0.111)	(0.125)	(0.229)
ln(Sales)	-0.263**	-0.185	-0.359
	(0.114)	(0.136)	(0.326)
Constant	3.472*	1.926	6.039
	(1.995)	(2.381)	(7.134)
Observations	1565	1311	254
R-squared	0.613	0.6	0.525

- Dependent variable: log of citation-weighted patents
- Cluster-adjusted robust standard errors
- *** *p<0.01,* ** *p<0.05,* * *p<0.10*
- Estimates for Year and Industry indicator variables omitted from results

Table 6: Blockbuster Patents Analysis

Sample restriction:	Entire sample	1st quartile	2nd quartile	3rd quartile	4th quartile	≥90th percentile	≥95th percentile	99th percentile
Lower bound (citation frequency)		0	2.71	6.4	13.6	25.6	37.04	72.58
ln(R&D)	0.922***	0.471***	0.496***	0.519***	0.698***	0.636***	0.606***	0.424***
	(0.0311)	(0.0270)	(0.0259)	(0.0257)	(0.0312)	(0.0377)	(0.0461)	(0.0631)
ln(IT)	0.178***	0.249***	0.260***	0.183***	0.119***	0.0351	0.00833	0.0145
	(0.0474)	(0.0403)	(0.0391)	(0.0376)	(0.0449)	(0.0497)	(0.0563)	(0.0676)
ln(Sales)	-0.240***	0.0887**	0.0426	0.0634	-0.142***	-0.117**	-0.155***	-0.159**
	(0.0505)	(0.0422)	(0.0409)	(0.0402)	(0.0473)	(0.0528)	(0.0599)	(0.0731)
Constant	2.649***	-6.562***	-5.765***	-4.756***	-0.246	0.282	1.316	1.823
	(0.786)	(0.662)	(0.633)	(0.630)	(0.727)	(0.819)	(0.964)	(1.143)
R-squared	0.626	0.613	0.615	0.610	0.545	0.465	0.376	0.255
Observations	1809	1591	1632	1629	1470	1078	786	348

- Dependent variable: log of citation-weighted patents using 5-year capped citation window
- All estimations use cluster-adjusted robust standard errors
- *** *p<0.01,* ** *p<0.05,* * *p<0.10*
- Estimates for Year and Industry indicator variables omitted from results

ONLINE APPENDIX

This appendix reports several robustness checks that supplement our analyses in the paper. First, we test for the influence of lagged IT and R&D on current innovation output. Although it is possible that innovation output responds slowly to variation in KPF inputs, we did not find evidence of a consistent lag structure for either variable. This is likely due to the very stable nature of both R&D expenses and IT capital flows within firms over time. Our results confirm prior research on the slowly-evolving relationship between R&D and patent output (Hall et al. 1986).

Second, we wish to verify that our model is not sensitive to the adjustment methods for patent citations. We re-estimate our model using unadjusted citation counts and unadjusted patent counts. We find that in both cases the results are generally similar to the OLS estimates using citation-weighted patents (Table A1). Using a Poisson regression for count data, we find the R&D elasticity to be 0.883 and 0.592 for citations and patents, respectively. The estimates for IT elasticity are 0.370 and 0.452, respectively. All estimates are significant at the 0.10% level. However, these larger estimates do not account for the quality differences among patents or the panel nature of the data, which we have found tends to reduce the magnitude of the IT elasticity estimates.[19]

Third, to address the concern that our 1.5-digit SIC industries insufficiently capture industry-level sources of unobserved influential factors, we re-estimate the model using the 19 2-digit and 73 3-digit SIC industry codes as control variables. We find that the inclusion of this many additional intercepts reduces the significance of our estimate of IT capital below the 10% level (Table A2). Given the lack of efficiency in the clustered standard errors approach, this result is not surprising; as the number of intercepts increases, their share of variance explained rises at the expense of our IT coefficient estimate. However, the industry controls themselves are, for the most part, statistically significant. This effect is

[19] We repeated our unweighted patent counts analysis using OLS and 2SLS models. The estimates remain similar in sign, relative magnitude, and significance level to the estimates made using citation-weighted patent counts.

robust to 2-digit and 3-digit SIC industry fixed effects. However, as the number of intercepts increases, their share of variance explained rises at the expense of our IT coefficient estimate.

Finally, all estimations were repeated with the patent citations restricted to a 5-year window. The coefficient estimates and R-squared values are qualitatively similar in all cases. This result reinforces the validity of weighting patent output by citations received, since the results are robust to the length of time each patent is allowed to accrue citations.

Table A1 – Poisson regressions

VARIABLES	1 Dependent Variable: Raw citations	2 Dependent Variable: Raw patents
lnrd	0.883***	0.592***
	(0.00115)	(0.00351)
lnit	0.370***	0.452***
	(0.00145)	(0.00474)
lnS93d	-0.393***	-0.152***
	(0.00138)	(0.00440)
Constant	3.572***	-3.581***
	(0.0240)	(0.0775)
Observations	1839	1839
*** p<0.01, ** p<0.05, * p<0.10 Standard errors in parentheses Year and 1.5-digit industry controls omitted from results		

Table A2 – Granular Industry Controls

VARIABLES	1 2SLS 1.5-digit SIC controls	2 2SLS 2-digit SIC controls	3 2SLS 3-digit SIC controls
lnrd	0.896***	0.901***	1.002***
	(0.0769)	(0.0822)	(0.136)
lnit	0.198*	0.107	0.166
	(0.111)	(0.106)	(0.118)
lnS93d	-0.263**	-0.138	-0.291
	(0.114)	(0.123)	(0.181)
Constant	3.472*	2.140	4.034
	(1.995)	(2.282)	(3.531)
Observations	1565	1565	1565
R-squared	0.613	0.650	0.717
*** p<0.01, ** p<0.05, * p<0.10 Standard errors in parentheses. Year and industry controls omitted from results			