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Information Technology and Trademarks: Implications for Product Variety

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This paper examines the relationship between information technology (IT) and trademarks. Using an 11-year panel data set (1987–1997) of IT capital stock, trademark holdings, and other measures for 116 Fortune 1000 manufacturing firms, we find that IT contributes to higher trademark holdings. Further, we find evidence suggesting that firms with more IT capital tend to apply for more new trademarks and retire existing trademarks more quickly, leading to a shorter trademark life cycle. Because trademarks are mainly used by firms to communicate differences among similar products to the marketplace, these results suggest that the business value of IT can be realized in greater product variety.

Key words: business value of IT; trademark; competitive advantage; product variety
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1. Introduction

Intangible assets, such as brands, organization, capabilities, and knowledge, represent an ever-increasing source of economic value in modern economies. For instance, the ratio of firm market value to the book value in S&P 500 companies has risen from about one at the beginning of 1980s to well over four in the 1990s (Lev 2001). The increase observed in intangible assets is coincident with significant increases in the stock of computer capital and investments in computers. The Bureau of Economic Analysis reports a doubling of business computer investment from $33.6 to $73.6 billion annually from 1987 to 1997, which, after accounting for the price-performance increases in computers, represents a 14-fold increase in real computer investment over this period.[1] Over the same period, the total capital stock (in current dollar terms) of computers, software, and communications equipment has risen 87% and, by 1997, represented 4% of all fixed assets and approximately 20% of equipment stock.[2] Through 2009, this proportion has remained roughly the same (about 21%) but investment levels in computers continue to grow (at about $120 billion annually in nominal terms in 2010).

A number of scholars have argued for and demonstrated a link between computer investments and intangible values (Bharadwaj et al. 1999). Part of the explanation is that components of information technology (IT) investment, such as some types of internally produced software, are intangible assets themselves, and these investments have been growing (Saunders 2010). However, there is increasing evidence that additional intangible assets are being created alongside IT investment, such as investments in organizational change complementary to IT (Brynjolfsson et al. 2002). Recent work has also shown a direct link between IT investment and innovative activity (Kleis et al. 2012), leading to a greater accumulation of intangibles.

In this study, we examine the relationship between IT and trademarks, one of the most important intangible assets of a firm. Prior work has shown that trademark holdings have a substantial relationship with overall firm market value (Seethamraju 2003), therefore representing part of a firm's intangible assets. Trademarks are used to describe and distinguish products in the marketplace. Consequently, trademarks are not truly stand-alone intangible assets, but are closely linked to firms' product portfolios. Firms with a broader product portfolio, or greater product variety, can utilize a greater number of trademarks to help consumers distinguish among their own products as well as the offerings of their competitors.

[1] Data available from http://www.bea.gov/national/info_comm_tech.htm (accessed June 2010).

[2] Calculations from Table 2.1 (Fixed Asset Tables), http://www.bea.gov/national/FA2004/ (accessed February 2011).

Firms can strengthen the value of trademarks with successful products. Indeed, the investments needed to obtain a trademark are relatively small (on the order of a few thousand dollars), compared to the investments needed to design, develop, manufacture, and deploy the products described by a trademark.

Although IT provides no specific advantage in the process of applying for a trademark per se, it does have a significant influence on the process that enables a firm to develop and introduce distinctive products that lead to the application for a trademark. Our primary empirical strategy is to estimate the relationship between a firm's investments in IT and the firm's trademark holdings, which can be measured directly through publicly available data. We will then use these results to make inferences about the relationship between IT and product variety, a relationship that has proven to be difficult to measure, especially across firms and industries. Clearly, our hypothesized relationship is only as strong as the link between variety and trademarks. As evidence for this link, we provide a review of the relevant literature, results from interviews with lawyers and trademark officers, examples from our data, and a small sample empirical analysis.

Our primary data is an 11-year (1987–1997) balanced panel data set of IT capital stock, trademarks, and relevant control variables for 116 Fortune 1,000 manufacturing firms. We find that, controlling for other factors, firms with greater IT capital tend to have a higher level of trademark holdings, indicating greater product variety. Furthermore, we find that IT contributes to an increased rate of new trademark applications but a lower five-year survival rate among the trademarks registered through these applications, suggesting shorter product life cycles.

This study contributes to the stream of research on the business value of IT (e.g., Barua et al. 1991, Kauffman and Kriebel 1988),[3] especially recent literature that emphasizes the role of organizational complements (Melville et al. 2004). It has been hypothesized that facilitating greater product variety is one way in which IT has contributed toward a shift to modern manufacturing (Milgrom and Roberts 1990). It may also be a significant source of unmeasured IT value (Brynjolfsson and Hitt 2000, Bresnahan et al. 2002). However, with the exception of the economy-level analysis in Brooke (1991), these conjectures have not been tested. Using the trademark data at firm level, we hope to empirically test these conjectures.

The rest of this paper is organized as follows. In §2, we summarize related literature and develop our research hypotheses. We describe the data set in §3 and report the results of our empirical analysis in §4. Section 5 offers our conclusions and recommendations.

2. Background

In this section, we examine how IT should be associated with trademarks via products. We first summarize the mechanisms by which IT can influence a firm's product strategy. We then provide an overview of our trademark data and explain the extent to which trademarks might reflect a firm's product variety level. Combining all this, we derive testable hypotheses of the relationship between IT and trademarks.

2.1. IT and Product Variety

The strategic importance of product variety to a firm is well documented (Lancaster 1990). Research in marketing has found that product variety can significantly influence consumer demand (Feinberg et al. 1992, Fader and Hardie 1996, Hui 2004, Berger et al. 2007). Operations management researchers have further linked the presence of higher product variety to higher firm performance (Kekre and Srinivasan 1990, Bayus and Putsis 1999, Bayus et al. 2003). Product variety can also be used strategically to preempt entry of potential competitors (Dewan et al. 2003, Boulding and Christen 2009). Studies in strategic management have found that product variety has important implications for firm survival (Cottrell and Nault 2004, Dowell 2006, Sorenson et al. 2006).

However, the benefits of variety can be offset by higher operational costs or greater operational complexity. Specifically, prior work has linked greater variety to lower production efficiency (Fisher and Ittner 1999, Thonemann and Bradley 2002), as well as greater costs and effort required for product design (Ramdas 2003). Others have linked variety to greater overall costs along a number of dimensions such as production and inventory holding costs (Skinner 1974, Banker et al. 1990). Finally, moving to a greater mix of products often entails costly changes in aspects of operations such as supply chain management practices (Randall and Ulrich 2001).

Theorists have argued that improvements in IT-enabled product design, production, and inventory management have facilitated the shift from low-variety mass production to high-variety, flexible "modern manufacturing" (Milgrom and Roberts 1990). Consequently, a reduction in the cost of offering greater variety, facilitated by advances and investment in IT, can alter the cost-benefit trade-off for product variety and lead to a higher optimal variety level (Dewan et al. 2003). In this analysis, we focus on the role of IT because it is closely linked to increased variety and also because improvements in the capabilities of IT over the last three decades have likely exogenously driven the increased levels of variety observed in U.S. firms.

[3] For reviews, refer to Stiroh (2002) and Banker and Kauffman (2004).

2.1.1. IT and Variety Creation. We follow the framework of an excellent review by Ramdas (2003) to discuss the major mechanisms by which IT is associated with greater variety. IT can potentially influence three major components of variety creation: concept development, product design, and project management.

Concept Development. The initial step of variety creation is concept development. A firm must identify opportunities that are not fulfilled by existing products and define product specifications. It has been established that data communications as well as database and visualization technologies facilitate knowledge sharing, and that IT, broadly defined, is associated with the formalization, storage, and spread of knowledge (Liberatore and Stylianou 1995). All of these capabilities can be harnessed to aid and facilitate the concept development process. IT can support the concept development processes by allowing a firm to integrate knowledge from marketing and engineering, which has been identified as important for product development (De Groote 1994).

Product Design. Product design is the process of moving a product from a concept to a production-ready prototype. This includes determining product architecture, designing components and modules, and testing performance. Computer-aided design (CAD) facilitates the design process (Joshi and Lauer 1998), and digital prototyping speeds the process of obtaining feedback from customers or other stakeholders (Dahan and Srinivasan 2000, Loch et al. 2001). Both of these technologies have become increasingly common in the last two decades (U.S. Census Bureau 1988), and examples of software supporting product development have been discussed in the marketing literature (Rangaswamy and Lilien 1997). Further, IT can help capture, analyze, and utilize knowledge from customers, which is key to product design (von Hippel 1998).

Project Management. Normally, a large firm will have multiple products under development at any given time and, as such, the task of managing development activities can become quite complicated (Girotra et al. 2007). Because the process of managing multiple concurrent development programs is information intensive, computer-enabled project management tools (such as those that incorporate PERT or Gantt concepts) can improve performance in large-scale project management and aid in coordinating development efforts and allocating development resources across products.

2.1.2. IT and Variety Implementation. Computer-based technologies have long been employed for automating production processes and coordinating internal production operations. In addition, they are increasingly being deployed for supply chain coordination. These technologies may help reduce the production efficiency "penalty" of greater variety (McCutcheon et al. 1994, Zipkin 1995, Thonemann and Bradley 2002).

Production Capabilities. Flexible manufacturing systems (FMS) reduce setup times and costs associated with the development of a broader product line (Kelley 1994, Stalk and Hout 1990). This is most evident in automobile industry (Clark and Fujimoto 1991) where production automation technologies such as materials requirements planning (MRP) and manufacturing resource planning (MRPII) further reduce the marginal cost of production complexity (Gerwin 1993).

Supply Chain Coordination. Greater product variety typically requires utilization of a greater variety of materials and components in the production process (Randall and Ulrich 2001). Moreover, as firms begin to offer more variety, they are likely to be transitioning from "functional products" to "innovative products" (Fisher 1997), which often require faster response to changing market conditions. Although these requirements were originally met by technologies such as electronic data interchange (EDI) (Srinivasan et al. 1994), firms have more recently made heavy investments in supply chain management systems (Aral et al. 2006).

Portfolio Management. When a firm's product line broadens, it becomes increasingly complicated to manage the product portfolio. Researchers have used attribute-based models to examine the product portfolio decisions (Green and Krieger 1989) in order to maximize revenues. In recent years, scholars have suggested that both supply side and demand side factors need to be considered to avoid cannibalization in product portfolio (Netessine and Taylor 2007). Given the complexity of the problem, identifying the optimal product portfolio composition is critical to a company's performance (Yunes et al. 2007). Product life-cycle management (PLM) software can integrate the related information and greatly facilitate product portfolio decisions, from the conception to the discontinuity of a product.

2.2. Trademarks

In the United States, trademarks are managed by the U.S. Patent and Trademark Office (USPTO). According to the USPTO, "A *trademark* is a word, phrase, symbol or design, or a combination of words, phrases, symbols or designs, that identifies and distinguishes the source of the goods of one party from those of others."[4] The definition of a trademark is codified in law through the Federal Trademark Act (Lanham Act of 1946, 15 U.S.C., §§1051–1127).

[4] http://www.uspto.gov/trademarks/basics/trade_defin.jsp (retrieved February 8, 2010).

The process of obtaining a trademark is straightforward. Typically, a firm first conducts a search to ensure the trademark is not confusingly similar to other registered trademarks, a condition which would prevent registration. Second, the firm files an application with the USPTO, which then examines the application for compliance with trademark regulations. If the application passes this examination, the trademark is published for a 30-day "opposition" period, during which other individuals or corporations can contest the assignment of the trademark. Finally, if there is no opposition, the trademark is registered to the applicant. The application process typically takes about one year and the industry participants we interviewed (see footnote 5) estimated the total cost to be less than $4,000 for a large firm, most of which are legal fees.

Legally, a registered trademark must be actively used in commerce. To enforce this requirement, the USPTO requires that the trademark holder reaffirm that the trademark is in use after 5 years, and then again every 20 years from the date of registration, by filing a document called an "Affidavit of Use."[5] If the firm cannot or does not show that the trademark is in actual business use at the time of renewal, the trademark will be cancelled. These practices have two useful implications for using trademarks as a measure of product variety. First, the requirement that a trademark must actively be used in commerce implies that trademarks are associated with actual products. Second, the requirement to periodically reaffirm a trademark enables the duration of use of a trademark to be estimated, as will be discussed in more detail later.

To understand the motivations for firms to register trademarks, we interviewed attorneys who specialize in trademark law, trademark officers responsible for managing trademarks for their firms, and officers of the USPTO.[6] The consensus among these sources is that trademark applications are strongly associated with new product development. The primary reason a firm would apply for a new trademark is to communicate distinctions among products to consumers, especially for new products. The close link between trademark and product differentiation is further reflected in scholarly work. Chamberlin (1933) recognized the importance of trademarks as means of product differentiation. Miaoulis and D'Amato (1978) emphasize the role of trademarks in distinguishing among similar products, and point out that infringement of a firm's trademark by competitors can lead to consumer confusion. Numerous studies in marketing examine the branding issues related to new products (e.g., Tauber 1981, Dickson and Ginter 1987), where brand and trademark are often used as rough synonyms (Landes and Posner 1987). From an economic standpoint, all this suggests that trademarks are a mechanism by which firms communicate product differentiation. Therefore, just as patents have been used as a measure of the innovative output of research and development (R&D) (see, e.g., Jaffe 1986), trademarks may play a parallel role in capturing product differentiation (Brooke 1991).

To illustrate the connections between products and trademarks, consider the consumer product lines offered by Procter and Gamble (P&G) (Figure 1). P&G is broadly organized into business units (such as personal and beauty, baby and family, and health and wellness), which span several industries. In prior studies of firm diversification, this would be the level at which diversification would be measured (e.g., Rumelt 1974, Montgomery 1982). Within these business units (for instance, the baby and family unit), there are many different product families associated with major brands, such as Puffs and Pampers. Within the Pampers brand, there are differentiated products with distinctive features, such as Baby Dry and Easy Ups diapers, each of which carry distinctive trademarks. Our analysis of trademarks corresponds to this level of the product hierarchy. Finally, there are different packages for these differentiated products, which are reflected in different stock keeping units (SKUs). Product level, "scanner data" studies in marketing (see, e.g., Fader and Hardie 1996 for a study of fabric softeners) work at this level.

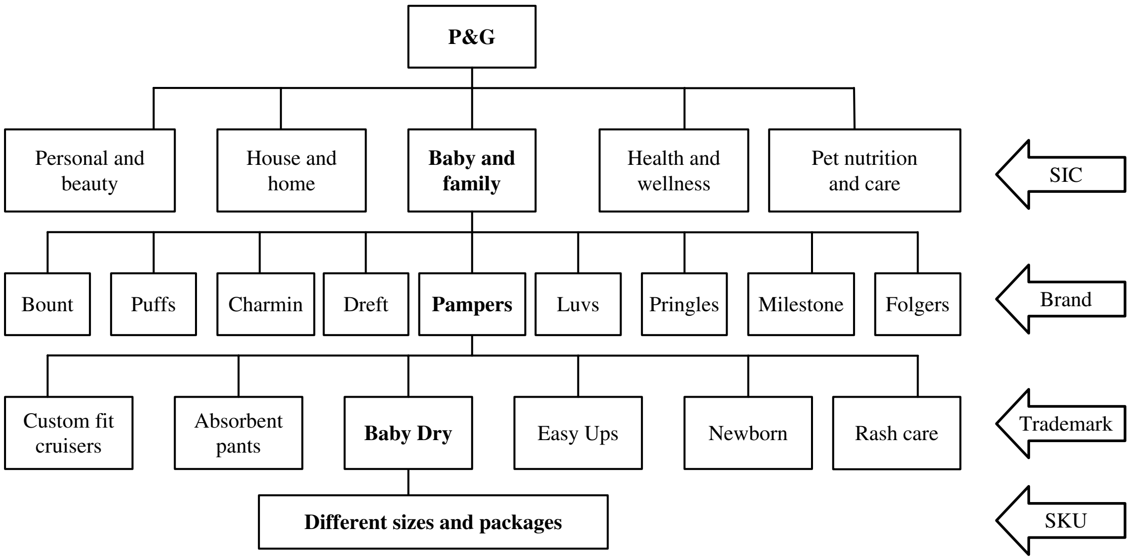
Our trademark measure represents an intermediate level between industry-related diversification measures and operational level product stocking decisions. This level appears to most closely correspond to product differentiation in the sense used in prior economic models. A few other studies have been conducted at this level of analysis, but they generally rely on industry specific data such as the number of application categories in software (Cottrel and Nault 2004) or the number of manufacturing product lines (Cachon and Olivers 2010). Such data is not widely available and cannot be readily measured for a large number of firms or meaningfully extended across industries. In contrast, trademarks are publicly available over a very broad historical timeframe (from 1884 to present) and encompass a vast array of products across all industries. Therefore, we believe this largely untapped data resource[7] can generate new insights pertaining to a firm's product variety strategy.

[5] Since November 1989, this period has been shortened to 10 years.

[6] We thank the International Trademark Association, the 2004 Trademark Administrators Conference, and the U.S. Patent and Trademark Office for their assistance.

[7] Brooke (1991) was the first effort we know to tie trademarks to variety in the information systems literature. However, his work focused on the total number of trademarks at economic sector level and did not consider the potential for constructing these measures at the firm level.

Figure 1 **Product Variety at Procter and Gamble (P&G)**



To further validate the connection between trademarks and variety, we obtained data from a recent study that investigated firms' product market activities. A survey specifically asked informed respondents to rate their firm's product variety in absolute levels and in comparison to their industry peers. Although only 33 of the firms in our analysis were captured in this survey, the rank order correlation between trademark count and firm product variety is strong at 0.67 ($p < 0.001$).[8] This provides further indication that our trademark measures are capturing at least a portion of product variety.

Nonetheless, there are some significant limitations with trademarks as a measure of variety. First, not all variety may be captured by trademarks as multiple products can be offered under the same trademark. Second, the value of trademarks varies significantly and, unlike patents that can be evaluated by examining citations, it is challenging to estimate the importance of any particular trademark. Third, there may be endogenous differences in firms' propensity to apply for trademarks. We try to address these concerns in our data construction and empirical strategy.

2.3. Summary

As discussed above, IT should facilitate the creation and management of greater product variety. Given that the price of IT investment has been steadily and exogenously declining for more than three decades, we would expect firms to make greater investments in IT, which in turn should enable firms to offer greater variety. The higher level of product variety should manifest itself in three ways. First, the overall level of product variety at any point in time, as reflected in total trademark holdings, should be higher. Second, firms transitioning to a higher level of product variety should show greater new product introduction activity, which would appear in our data as a higher level of new trademark applications. Third, greater product variety may be associated with greater turnover in products if new products are introduced to replace existing products, which would appear in our data as a shorter trademark life cycle. These three hypotheses will be examined in our empirical analysis.

3. Data

Our data set is comprised of three sources: (1) trademark data from the USPTO over the 1987–2003 period (2003 data is needed to calculate the survival rate for trademarks registered in 1997); (2) a panel of large manufacturing firms detailing IT capital levels over the 1987–1997 period; (3) Compustat for operational and financial measures.

3.1. Trademarks

The USPTO maintains an extensive database of trademarks dating back to 1884. These data include a description of the trademark, the company to which it is assigned, and information about when the trademark was registered, abandoned, cancelled, or expired. These dates, combined with the rules for

[8] This survey conducted in 2009 examined human resource and technology practices in large firms and was jointly sponsored by McKinsey, MIT, and the Wharton School. The exact question was, "How would you rate the number of products you offer in your primary business in absolute terms?" The response scale for the former was a range of one to five with one being "single product" and five representing "multiple, broad product lines." Of the 213 respondents on the human resource practices survey, 33 were in our sample. Most of the firms surveyed are not in manufacturing section and thus not matched.

how trademarks are reevaluated, enable the number of trademarks to be determined for each registrant in each year.

We begin our trademark data set construction by matching all company names from trademark database to the standardized list of company names (including parent companies and all subsidiaries that appear in the Compact Disclosure Database). We follow a procedure similar to that employed in the literature on the economics of patents (Hall et al. 1988), combining algorithmic text matching with a manual review of unmatched names. After matching trademarks to companies, we calculate each trademark's life span to determine whether a certain trademark was active in a certain year, and then aggregate all active trademarks to determine the total number of trademarks that a firm uses in a certain year.

Trademarks, like patents, can vary significantly in their value. However, unlike patents, for which the number of citations by other patents can be used to judge relative "importance" (see Jaffe and Trajtenberg 2002), there is no comparable way of assessing the importance of a trademark. We therefore take several steps to try to limit the heterogeneity of the trademarks. Because most of our arguments about the IT-variety link are related to physical differences in products, we restrict our analysis to trademarks that correspond to physical products and exclude "service marks" that can be applied only to services. Second, we restrict our sample to manufacturing firms where product differentiation appears as physical product differences, consistent with our earlier arguments. Thus, our sample is restricted to firms that operate under the two-digit standard industrial classification (SIC) codes 20 to 39. Third, the fact that trademark status must be reaffirmed over time allows us to more accurately measure the total number of trademarks that are actually used by a company at a certain time point. Our measure of trademark holding includes only trademarks that are marked as "registered" in a certain year. After a trademark is expired (registered trademark not renewed after the full term) or cancelled (the firm failed to reaffirm the trademark after five years), it is no longer included in the count. Abandoned applications (registration never completed) are excluded from our data construction as well.

The underlying process of trademark generation can best be described as a flow process. In any given time frame, firms are applying for new trademarks, renewing some, and allowing others to expire. However, we can only observe this process as a series of data "snapshots" taken over time. The principal events are registration when the trademark is created, followed by the first evaluation at the fifth year renewal, during which the USPTO either reaffirms the trademark or marks it as cancelled. We therefore utilize two kinds of information to determine trademark life span for a certain firm (i) in a certain year (t): (1) how many new trademarks are registered in that year, which we denote as N_{it}; and (2) among these new trademark applications, how many get cancelled at the end of fifth year, which we denote as C_{it}. To translate these two observations into an estimate of the life span of a trademark, we utilize a survival analysis approach using the constant hazard survival function. This approach has the advantage of requiring an estimate of only a single parameter, thus making it possible to construct a trademark duration estimate for each firm. The constant hazard survival function model implies an exponential failure time for a trademark. Thus, the probability that a trademark will "die" before the end of the fifth year is given by

$$P(T<5)=1-\exp\left[-\int_0^5 \lambda\, ds\right],$$

where λ is the hazard rate.

We can estimate a firm-specific survival rate parameter by equating the observed five-year trademark survival proportion to the predicted ratio from the model. In other words, we set λ to fit $1-\exp[-\int_0^5 \lambda\, ds] = C_{it}/N_{it}$. We then calculate the expected number of trademarks that are still in use for each year after registration and aggregate this expected value to generate an annual trademark count for each firm, which is denoted as $TM\_Holding_{it}$.

To examine the impacts of IT on trademark applications, we perform a count of new trademark applications each year for each firm, which is denoted as $TM\_Application_{it}$. We exclude applications that were abandoned during the registration process.

Finally, to test whether IT tends to shorten the life cycle of trademarks, we construct another variable $TM\_Survival_{it}$, which is the logistic transformation of the rate of trademark applications that passed the five-year threshold. We denote y_{it} as the portion of trademarks applied by firm i in year t that later passed the five-year threshold:[9]

$$TM\_Survival_{it}=\ln\left(\frac{y_{it}}{1-y_{it}}\right).$$

[9] We use the logit function because it is frequently used when the dependent variable is a percentage (see Liao 1994). Because the odds are not defined when $y_{it}=0$ or $y_{it}=1$, we replace y_{it} with the next closest value in the sample (0.03 and 0.95, respectively) to avoid losing observations. Our results are not sensitive to this adjustment. Findings are very similar when replacing 0.001 and 0.999. Further, using the original y_{it} as dependent variable produces similar findings.

3.2. IT Measures

Although our trademark measure has been newly developed for this research, we rely largely on existing measures and data for IT and other production characteristics. Our measures of IT use were derived from the Computer Intelligence Info Corp (CII) installation database. These data have been used in prior firm-level studies on IT value by Lichtenberg (1995), Brynjolfsson and Hitt (2003), and Chwelos et al. (2010), among others. For decades, CII has conducted a telephone survey geared at capturing a full inventory of the specific pieces of IT equipment in use for firms in the Fortune 1,000. Approximately 25,000 sites have been surveyed every year since 1987. After a numerical count is obtained, CII then assigns a market value to each piece of equipment in order to obtain a total IT capital stock measure.

There are several limitations inherent in this approach. For instance, IT data do not include all types of information processing or communication equipment and are likely to have omitted equipment that was purchased by individuals or departments without the knowledge of information systems personnel or that is owned or operated off-site. Additionally, the IT data exclude investments in software and applications. However, to the extent that different types of IT investments are complementary, higher measures of our IT equipment variables are likely strongly associated with higher levels of other variables. Therefore, these measures are suited to revealing the qualitative relationship rather than specific per-dollar marginal product. Variations in the ratio of IT equipment to other IT investment will likely introduce some random variation into our measures, which will, according to standard results on the effects of errors in independent variables in regression models, tend to skew our results toward the conservative (biased toward zero) end of the spectrum.

Our CII data set covers the span of years from 1987 to 1997. However, from 1995 onward, CII altered its operational definition of IT capital to reflect a narrower scope of computer hardware and stopped tabulating computer stock market values, making the IT capital measures inconsistent before and after year 1995. We adopt the procedure demonstrated in Chwelos et al. (2010) to provide internally consistent estimates of IT stock from 1995 to 1997. This method involves using a hedonic regression on existing data from 1987–1994, adjusting the hedonic coefficients by aggregate-level price trends for different types of hardware, and then using these adjusted hedonic coefficients to impute a value of different types of hardware going forward. Thus, our IT capital stock data include the actual raw data (adjusted for inflation) through 1994, and the imputed capital stock based on equipment counts from 1995 to 1997. We also include control variables for year in all of our specifications to further address temporal heterogeneity in our measures.

3.3. Other Variables

To complement the trademark and IT measures, we incorporate other accounting and financial variables from Compustat and Eventus. These variables include total assets, R&D expenditure, advertising expenditure, labor cost, and stock price volatility (*Beta*). Advertising expenditure and primary industry are taken directly from Compustat. Stock price volatility is taken directly from Eventus.

Labor expense is taken from Compustat where reported (about 30% of firms), and is computed based on number of employees and an industry-specific average wage provided by the Bureau of Labor Statistics (BLS) at the two-digit industry level for each year when this information is not directly available. This series is then deflated by the price index for total compensation (Council of Economic Advisors 1999). Capital age is based on the ratio of a three-year average of cumulative depreciation to current depreciation. Ordinary capital is computed as gross property plant and equipment deflated by a BLS industry-specific (two-digit level) capital deflator assuming that all capital was invested at the current time period minus the average age. The methods for constructing capital age and ordinary capital are consistent with prior work in R&D and IT productivity (Hall 1990, Brynjolfsson and Hitt 2003). R&D capital stock is constructed from a 20-year series on R&D expenditure using methods proposed by Hall (1990). The initial year expenditure is multiplied by five to represent an estimate of initial stock (implying a 20% depreciation rate) and then subsequent year investment is deflated to constant dollars and added to the prior year stock after allowing for a 20% annual depreciation. The deflator is based on an average of R&D labor costs and materials costs proposed by Hall (1990). We use a dummy variable to indicate the missing values in R&D.

Given the 11-year time series that we employ, it is possible that the firms we assessed have changed considerably over time because of merger or acquisition (M&A) activity. To ensure consistency in our sample over time, we excluded any firm that had a year-over-year change greater than 50% in assets in a single year. This should adequately eliminate the effects of M&A or other major restructuring activities. Use of different thresholds (30%, for example) yields similar results.

Finally, we then exclude firms that have missing values in key measures. Our final sample includes 116 firms over the 11-year period from 1987 to 1997, which results in a balanced panel of 1276 firm-year observations. The balanced panel allows us to better model the error structure in our estimation procedures, and to be more confident that our results are

Table 1 Descriptive Statistics of Major Variables

Variable	Unit	N	Mean	Std. dev.
IT Stock	\$mm, 1994 constant	1,276	30,172.55	58,563.13
PC	Count	1,276	4,708.65	7,447.79
Term	Count	1,276	6,611.98	10,900.82
Nodes	Count	1,276	1,788.67	4,295.14
TM_Holding	Count	1,276	175.38	191.01
TM_Application	Count	1,276	12.44	14.83
Fifth Year Survival Rate	Ratio	1,146	0.62	0.28
TM_Industry_Average	Count	1,276	44.76	28.50
Capital	\$mm, 1994 constant	1,276	7,236.72	18,442.61
Labor_Intensity	Ratio	1,276	0.47	0.54
Herfindahl	Index	1,276	0.07	0.08
R&D	\$mm, 1994 constant	897	1,265.86	1,885.22
Ads	Ratio	1,061	0.03	0.03
Capage	Index	1,275	6.82	2.40
Beta	Index	1,048	0.97	0.39
Debt_to_Equity Ratio	Ratio	1,139	0.88	10.17

not driven by changes in the sample over time. However, analysis of an unbalanced panel yielded similar results. A summary of our key variables appears in Table 1. Table 2 provides the industry distribution of companies in our sample, and a comparison with the population in Compustat. As can be seen, our sample is largely representative in terms of the industry distribution. Correlations of variables are provided in Table 3.

Table 2 Sample Composition

Two-digit SIC code	Sample in the paper: Frequency	Sample in the paper: Percent	Compustat[a]: Frequency	Compustat[a]: Percent
20	14	12.07	387	5.16
21	1	0.86	23	0.31
22	2	1.72	119	1.59
23	1	0.86	164	2.19
24	2	1.72	88	1.17
25	6	5.17	94	1.25
26	7	6.03	165	2.2
27	3	2.59	244	3.26
28	22	18.97	1,268	16.92
29	6	5.17	105	1.4
30	3	2.59	219	2.92
31	0	0	43	0.57
32	2	1.72	124	1.65
33	8	6.90	228	3.04
34	5	4.31	263	3.51
35	8	6.90	1,090	14.54
36	10	8.62	1,243	16.59
37	10	8.62	344	4.59
38	5	4.31	1,063	14.18
39	1	0.86	220	2.94
Total	116	100	7,494	100

[a]Based on year 1990 data.

4. Empirical Analysis

4.1. Model Specification

We use the following general framework to test our hypotheses:

$$TM = \beta IT + \gamma X + \varepsilon, \qquad (1)$$

where *TM* is the dependent variable (either *TM_Holding*, *TM_Application*, or *TM_Survival*), *IT* is a measure of IT capital, and *X* is a vector of control variables. One challenge in getting an unbiased estimate of β is that firms may differ in characteristics that influence both the overall level of IT capital and product variety simultaneously. If these confounding factors are not controlled for, they could lead to spurious correlation between *IT* and *TM*. These variables can be divided into two broad groups: firm-specific factors and environmental factors.

The firm-specific factors we consider are investments and expenditures on R&D, advertising, capital, and labor. We include R&D because firms that are investing in innovation will likely spend more on IT because R&D is an IT-intensive activity in most industries; these firms will also likely have a greater number of trademarks due to their product innovation activities. We capture R&D using our measure of R&D capital, as described earlier (variable *R&D*).

Because trademarks describe distinctions among products that are perceived by consumers, it is likely that these same firms are using other approaches such as advertising to communicate these product distinctions. Moreover, many of the systems that support marketing and advertising rely heavily on IT (e.g., customer data warehousing, customer relationship management systems, etc.). Consequently, we control for advertising (variable *Ads*), measured as the advertising-to-sales ratio. Firms typically do not report advertising expenses when they are negligible, so we replace missing values of this measure with zero.[10]

Larger firms have a greater production scale, which might provide advantages in the cost efficiency of IT investment or product line expansion. Expanding product variety in manufacturing usually requires expanding product lines (Kekre and Srinivasan 1990), investing in flexible manufacturing equipment (Fisher and Ittner 1999), or changing the supply chain structure (Randall and Ulrich 2001). We thus include a measure of *Capital*, an estimate of the productive capital stock of a firm. The measure is based on total property plant and equipment in constant dollars as

[10] We also examined alternative treatments to the missing value in *Ads* by filling with industry average, or adding a dummy variable indicating missing value. They produce very similar results.

Table 3 Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
IT Stock (1)	1															
PC (2)	0.92*	1														
Term (3)	0.50*	0.58*	1													
Nodes (4)	0.55*	0.44*	−0.21*	1												
TM_Holding (5)	0.37*	0.41*	0.32*	0.13*	1											
TM_Application (6)	0.32*	0.34*	0.23*	0.16*	0.82*	1										
Fifth year survival rate (7)	−0.20*	−0.24*	−0.10*	−0.07*	−0.17*	−0.20*	1									
TM_Industry_Average (8)	−0.11*	−0.06*	−0.03	−0.09*	0.32*	0.23*	−0.12*	1								
Capital (9)	0.59*	0.61*	0.45*	0.18*	0.32*	0.22*	−0.20*	0.28*	1							
Labor_Intensity (10)	−0.05	−0.09*	0.05	−0.11*	0.05	0.09*	0.11*	−0.48*	−0.61*	1						
Herfindahl (11)	−0.05	−0.11*	0.01	−0.10*	−0.23*	−0.23*	0.01	−0.18*	−0.05	0.11*	1					
R&D (12)	0.77*	0.80*	0.54*	0.23*	0.36*	0.34*	−0.24*	0.06	0.77*	−0.25*	−0.15*	1				
Ads (13)	0.07*	0.07*	−0.27*	0.37*	0.41*	0.43*	−0.14*	0.41*	−0.05	−0.02	−0.45*	−0.03	1			
Capage (14)	0.04	0.02	−0.05	0.12*	0.01	−0.09*	0.04	0.24*	0.31*	−0.51*	−0.06	−0.01	−0.04	1		
Beta (15)	0.16*	0.22*	0.34*	−0.18*	0.07*	0.14*	−0.18*	−0.01	0.28*	−0.01	−0.05	0.42*	−0.02	−0.21*	1	
Debt_to_Equity Ratio (16)	0.36*	0.34*	0.16*	0.25*	0.35*	0.22*	−0.12*	0.20*	0.27*	−0.04	−0.00	0.19*	0.17*	0.09*	−0.15*	1

Note. Pair-wise Spearman correlation is reported.
$^{*}p < 0.05$.

described earlier.[11] Labor is also a key factor input likely to influence new product introduction; it functions as another way of capturing firm size. Therefore, we include labor intensity (*Labor_Intensity*), which is defined as the ratio of labor expense to capital.

A number of factors in firms' external environments are likely to affect product variety level and may be simultaneously correlated with the level of IT investment. It is possible that there are within-industry competitive effects driving the level of trademarks. Firms may expand their variety in response to the level of variety offered by other firms. To control for this possibility, we include a measure of the overall level of trademark holdings for each industry in each year. Our variable, *TM_Industry_Average* is computed as the mean of trademark holdings for all Compustat firms in the same two-digit industry for each year. This calculation includes firms not in our sample because these firms likely affect the level of industry competition even if we do not have the full data on their IT activities that would allow them to be included in our sample. As a further control for industry competition, we include the Herfindahl index for each two-digit SIC firm for each year as a proxy for degree of competition (*Herfindahl*). The Herfindahl index is a standard measure of industry concentration and is calculated based on the sum of the squares of the ratios of each firm's sales to total industry sales on Compustat.

Finally, the macroeconomic environment might drive the demand for IT and trademarks in different time periods. Thus, we include year dummy variables in the regression. This subsumes any time-series factor common across firms (e.g., growth in U.S. GDP or interest rates) and controls for any general trends in IT or trademarks that might be present in the data.

This yields the following model:

$$
\begin{aligned}
&\log(TM\_Holding_{it})\\
&\quad = \beta_0 + \beta_1 \log(IT_{it}) + \beta_2 \log(R\&D_{it}) + \beta_3 Ads_{it}\\
&\qquad + \beta_4 \log(TM\_Industry\_Average_{mt})\\
&\qquad + \beta_5 \log(Capital_{it}) + \beta_6 Labor\_Intensity_{it}\\
&\qquad + \beta_7 Herfindahl_{mt} + year\_dummies_t + \varepsilon_{it}. \qquad (2)
\end{aligned}
$$

In the above specification, subscripts denote that these measures are across firms (i), years (t), and two-digit SIC industries (m). Because firms in our sample vary considerably in size, we transform all size-related variables using logarithms, including the dependent variable $TM\_Holding_{it}$.

Our estimation approach is based on addressing three potential problems in our data. First, our data involve repeated observations for the same firm over time, leading to potential correlation between the error terms within each firm panel due to random firm effects. Second, competitive effects or other shocks in one year may have persistent effects, leading to the possibility of firm-specific autocorrelation over time. Finally, with heterogeneous data, there is always the possibility of conditional heteroskedasticity. The Wooldridge test for autocorrelation (Wooldridge 2002) confirms the existence of first-order autocorrelation (AR1) (F-Statistic $= 104.74$). Breusch-Pagan test also reveals that heteroskedasticity is a concern ($\chi^2 = 372.46$). Given that autocorrelation and heteroskedasticity are likely to vary across firms,

[11] This differs from measures of assets that sometimes use a size control that includes nonproduction assets such as cash and does not account for inflation.

our principal estimates are performed using a using generalized least squares (GLS), which allows for a panel- (firm-) specific AR1 process and heteroskedasticity.[12] We include controls for time so that our results are robust to specification errors that could be created by macroeconomic effects common to all firms.

There are two additional possible endogeneity problems that we must also consider. First, firms may have persistently different levels of IT and variety that are not suitably addressed by our control variables. We therefore include firm-level fixed effects estimates. These are, however, likely to understate the overall relationship between IT and trademarks because they might eliminate a portion of the true relationship between IT and variety along with spurious relationships due to unobserved heterogeneity. We therefore also examine random effects estimation. Second, it is possible that firm-specific shocks (such as unexpectedly high demand) may enable a firm to simultaneously make investments in IT (such as flexible manufacturing) and extend product lines, resulting in greater variety. Alternatively, a firm anticipating a need for greater variety (due to some unrelated issue) may make greater investments in IT in anticipation of this effect. Either of these issues could lead to a correlation between IT level and the error term, leading to biased estimates. To address this form of endogeneity, we treat IT level as endogenous and utilize instrumental variables. The instrument set was chosen based on prior research (Brynjolfsson and Hitt 2003) and includes measures of the flexibility of the IT infrastructure (specifically the use of client server architectures that is proxied by the ratio of PCs to mainframe terminals and network nodes to PCs), the flexibility of a firm's production infrastructure (proxied by capital age), and the firm's cost of capital (proxied by the debt-equity ratio and stock market beta). All of these capture a firm's idiosyncratic ability to respond to increases in the need for IT. Because our preferred estimator does not include an instrumental variables variant, we utilize a two-step procedure in which we compute a fitted value of IT regressed on the instruments and then use this measure in our GLS regression employing the procedures described earlier.[13]

4.2. Findings

4.2.1. IT and Trademark Holding. Equation (2) posits that IT capital is associated with greater trademark holdings. The regression results are reported in Table 4. As stated above, all estimates we report are adjusted for panel-specific autocorrelation and heteroskedasticity unless otherwise noted. We find that the GLS estimate of the IT coefficient is 0.0580, which is significantly different from zero ($p < 0.01$). We next added individual firm effects into the model. We find that the positive relationship between IT and trademark holdings is still significant ($p < 0.01$) (column (2), Table 4), although the magnitude is smaller. This coefficient reduction is not surprising, as the fixed effects analysis eliminates sources of variation in IT and trademarks across firms, while also emphasizing the time dimension. Column (3) in Table 4 reports the random effects estimates. We find that IT's coefficient is significant at $p < 0.01$ level, and the magnitude is similar to that in the GLS.[14] Thus, the evidence suggests that IT is associated with a higher level of trademark holdings.

Table 4 **Relationship Between IT Capital Stock and Trademark Holding**

Dependent variable: Logarithm of trademark holding level with duration adjustment (*TM_Holding*)

Variable	(1) GLS	(2) GLS with fixed effects	(3) Random effects model[a]	(4) Instrumental variables
IT Stock	0.0580***	0.0157***	0.0668***	0.0536***
	(0.00917)	(0.00535)	(0.0149)	(0.0122)
R&D	0.244***	0.0853***	0.0865***	0.214***
	(0.0138)	(0.0182)	(0.0299)	(0.0147)
Ads	1.376***	0.0276	1.108***	0.860***
	(0.274)	(0.111)	(0.385)	(0.213)
TM_Industry_Average	0.629***	0.488***	0.676***	0.726***
	(0.0251)	(0.0371)	(0.0721)	(0.0251)
Capital	0.0212	0.0431***	0.104***	0.0713***
	(0.0139)	(0.0134)	(0.0268)	(0.0147)
Labor_Intensity	0.104***	−0.0235	−0.143***	0.137***
	(0.0291)	(0.0245)	(0.0291)	(0.0296)
Herfindahl	−1.939***	0.116	0.0772	−2.111***
	(0.173)	(0.186)	(0.300)	(0.227)
Constant	1.179***	1.489***	0.534	0.915***
	(0.164)	(0.173)	(0.345)	(0.187)
Other controls	Year	Year, Firm	Year	Year
Observations	1,276	1,276	1,276	1,046
Number of firms	116	116	116	98

Note. Panel specific AR1 and heteroskedasticity adjusted standard errors in parentheses unless otherwise noted.
[a] Huber–White robust clustered standard errors reported.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

[12] This process is implemented using *XTGLS* command in Stata 9.2. We also applied Poisson and negative binomial estimation, which produce very similar results.

[13] Theoretically, this causes a small reduction in degrees of freedom in our GLS estimation that could affect the estimates of some regression parameters, but these effects are negligible given our sample size.

[14] In our random effects estimation, the panel-specific AR1 standard error term would not converge. Therefore, we convert to the Huber–White robust clustered standard errors, which allows for arbitrary error structure.

To further validate the above findings, we now consider instrumental variables estimates. Because of the missing values of some of the instrumental variables (principally *Beta*), the sample is reduced to 98 firms in the estimation. The first stage regression has an adjusted R^2 of 0.85, which suggests that the IV regressions have reasonable power. In the IV regression, the IT coefficient is reduced slightly to 0.0536 (column (4), Table 4) but is not significantly different from the estimates provided by GLS. The coefficient is significant at 1% confidence level. Overall, we find a consistent positive relationship between IT and trademark holdings. Moreover, instrumental variables estimates are similar to the corresponding GLS estimates. This suggests that our results are not driven by endogeneity and supports a causal interpretation of our results.

Our control variables generally conform to expectations. We find that the coefficient of R&D capital is consistently positive and significant at the $p < 0.01$ level, indicating that firms with more R&D tend to have more trademark holdings. Similarly, firms that spend more on advertising tend to have more trademark holdings. This relationship is less robust than that of R&D, perhaps because of the volatility of advertising from year to year. Firm and industry average trademark holdings are strongly correlated ($p < 0.01$), as is the measure of industry competition (*Herfindahl*). This suggests that the competitive value of trademarks changes over time even within an industry, and that firms respond to the variety level of other firms by increasing their own variety. We also find that the capital is statistically significant and positive in most specifications, suggesting that this variable plays the role of a size control.

4.2.2. IT and Trademark Applications. The following specification is used to estimate IT's impact on new trademark applications:

$$\begin{aligned}\log(TM\_Application_{it}) &= \beta_0 + \beta_1 \log(IT_{it}) + \beta_2 \log(R\&D_{it}) + \beta_3 Ads_{it} \\ &\quad + \beta_4 \log(TM\_Industry\_Average_{mt}) \\ &\quad + \beta_5 \log(Capital_{it}) + \beta_6 Labor\_Intensity_{it} \\ &\quad + \beta_7 Herfindahl_{mt} + year\_dummies_i + \varepsilon_{it}. \qquad (3)\end{aligned}$$

Empirical results are reported in Table 5. We find supporting evidence for IT's role in enabling higher trademark application in the GLS, random effects, and IV estimations. The estimated IT coefficient ranges

Table 5 Relationship Between IT and New Trademark Applications

Dependent variable: Logarithm of trademark application count (*TM_Application*)					
	(1) GLS	(2) GLS with fixed effects	(3) Random effects model[a]	(4) Instrumental variables	(5) Negative model binomial with fixed effects[a, b]
IT Stock	0.104***	0.0345	0.148**	0.127**	0.133**
	(0.0354)	(0.0317)	(0.0579)	(0.0506)	(0.0607)
R&D	0.258***	0.0524	0.166**	0.254***	−0.0856
	(0.0370)	(0.0794)	(0.0677)	(0.0407)	(0.139)
Ads	7.741***	1.529*	2.671**	7.849***	2.844**
	(0.985)	(0.896)	(1.248)	(1.000)	(1.296)
TM_Industry_Average	0.457***	1.493***	0.545***	0.577***	1.542***
	(0.0621)	(0.173)	(0.122)	(0.0673)	(0.297)
Capital	−0.0614*	0.0593	−0.0494	−0.0118	0.129
	(0.0341)	(0.0665)	(0.0813)	(0.0424)	(0.116)
Labor_Intensity	0.355***	−0.0755	−0.00702	0.333***	−0.127
	(0.0562)	(0.0692)	(0.159)	(0.0656)	(0.141)
Herfindahl	−1.232***	0.311	−0.933*	−1.502***	1.028
	(0.248)	(0.698)	(0.486)	(0.280)	(1.019)
Constant	−0.744*	−4.664***	−1.127	−1.590***	−6.589***
	(0.419)	(0.824)	(0.796)	(0.514)	(1.399)
Other controls	Year	Year, Firm	Year	Year	Year
Observations	1,276	1,276	1276	1,046	1276
Number of firms	116	116	116	98	116

Note. Panel specific AR1 and heteroskedasticity adjusted standard errors in parentheses.
[a]Huber–White robust clustered standard errors reported.
[b]Dependent variable is the count of trademark application.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 6 **Relationship Between IT and Trademark Life Cycle**

Dependent variable: Logit of the survival rate at fifth year (*TM_Survival*)					
	(1) GLS	(2) GLS	(3) GLS with fixed effects	(4) Random effects model[a]	(5) Instrumental variables
IT Stock	−0.189***	−0.143***	−0.256	−0.196	−0.101
	(0.0493)	(0.0500)	(0.201)	(0.128)	(0.0812)
TM_Application		−0.207***	−0.239*	−0.201**	−0.161***
		(0.0387)	(0.123)	(0.0893)	(0.0460)
R&D	−0.0452	−0.0265	−0.0879	−0.0976	−0.137***
	(0.0435)	(0.0437)	(0.346)	(0.101)	(0.0494)
Ads	−3.163**	−1.737	0.625	−1.146	−0.770
	(1.539)	(1.520)	(3.093)	(2.297)	(1.550)
TM_Industry_Average	−0.442***	−0.389***	−1.203	−0.340**	−0.388***
	(0.0850)	(0.0834)	(0.871)	(0.169)	(0.0959)
Capital	−0.113**	−0.0921**	0.159	−0.0176	0.0327
	(0.0457)	(0.0467)	(0.321)	(0.105)	(0.0686)
Labor_Intensity	−0.405***	−0.325***	−0.565***	−0.316**	−0.187**
	(0.0850)	(0.0860)	(0.209)	(0.130)	(0.0918)
Herfindahl	−0.790	−1.308**	−5.212***	−1.521**	−0.0802
	(0.627)	(0.609)	(1.196)	(0.728)	(0.637)
Constant	5.625***	5.285***	8.029**	5.130***	3.427***
	(0.491)	(0.486)	(4.094)	(1.332)	(0.639)
Other controls	Year	Year	Year, Firm	Year	Year
Observations	1146	1146	1146	1146	963
Number of firms	116	116	116	116	98

Note. Panel specific AR1 and heteroskedasticity adjusted standard errors in parentheses.
[a]Huber–White robust clustered standard errors reported.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

from 0.104 to 0.148 ($p < 0.05$). Taking the IV estimate as an example, a 1% increase in IT is associated with a 0.127% increase in new trademark applications. The coefficient on IT remains positive after we add firm-specific fixed effects, although the estimates are no longer statistically significant. Among other variables, both *R&D* and *Ads* are positively correlated with higher trademark applications.

Because the number of trademark applications is count variable, we further examine the robustness of IT's impact on trademark applications using a count model. Because the variance of *TM_Application* is greater than the average, we apply the negative binomial model, similar to Fleming (2001). We also included firm-specific fixed effects. Robust clustered standard errors are reported to account for repeat observations from each firm. The results are reported in column (5) of Table 5. We find that IT's coefficient is positive and significant at $p < 0.01$ level, which renders additional support for the claim that IT leads to more trademark applications.

4.2.3. IT and Trademark Life Cycle. To examine the relationship between IT and the trademark life cycle, we use *TM_Survival* (the logarithm of fifth year survival odds) as the dependent variable. Given that we found that IT leads to more new trademark applications and that some of this likely represents product replacement, it is natural to think that more applications will lead to a lower survival rate for each application. To control for this confounding factor, we add *TM_Application* to the explanatory variables. Thus,

$$\begin{aligned} TM\_Survival_{it} &= \beta_0 + \beta_1 \log(IT_{it}) + \beta_2 \log(R\&D_{it}) + \beta_3 Ads_{it} \\ &\quad + \beta_4 \log(TM\_Industry\_Average_{mt}) \\ &\quad + \beta_5 \log(Capital_{it}) + \beta_6 Labor\_Intensity_{it} \\ &\quad + \beta_7 Herfindahl_{mt} + \beta_8 TM\_Application_{it} \\ &\quad + year\_dummies_i + \varepsilon_{it}. \end{aligned} \tag{4}$$

Estimation results are reported in Table 6.[15] We first report the findings without *TM_Application* as a control variable. The coefficient of IT is negative and significant at $p < 0.01$ level (column (1), Table 6). This suggests that firms with higher IT investments tend to have a lower rate of survival of newly obtained

[15] Notice that we lose about 10% observations because *TM_Survival* is not defined in some years due to no new trademark applications.

trademarks. Specifically, a 1% increase in IT leads to a firm's trademarks being about 0.17% less likely to pass the five-year threshold.

Table 6 (column (2)) reports comparable results when we control for the number of trademark applications. This additional variable has a negative coefficient, consistent with our conjecture that a high rate of product introduction leads to a higher rate of displacement of existing products. Nonetheless, the coefficient of IT, although a bit smaller, remains significant at the $p < 0.01$ level. It remains the same magnitude and is nearly significant in the random effects model ($p = 0.12$). The negative effect of IT on survival rate is also observed in the fixed effects model and the IV estimation, although these estimates are not significant at conventional levels.

Collectively, these results suggest that IT has two competing effects on the overall level of trademark holding. First, IT is associated with a greater rate of trademark applications, which leads to a higher level of trademark holding. Second, IT is associated with a shorter life span of trademarks, which leads to fewer trademark holdings. Our overall finding that IT is associated with greater total trademark holdings suggests that the former effect dominates the latter.

5. Discussion and Conclusion

In this study, we examine the relationship between IT and trademarks. Our results suggest that IT capital is associated with higher levels of trademark holdings. This effect persists after controlling for time trends as well as for other factors that might influence a firm's product variety level, including R&D, advertising intensity, labor intensity, and size. The findings remain consistent when an instrumental variables approach is used in estimation, thus supporting a causal interpretation of our results. Further, we find that IT is associated with higher levels of trademark applications, suggesting an increased rate of product introduction. We also find some weak evidence for an association between higher IT capital and shorter trademark life span, suggesting that IT enables companies to update their products more frequently. However, on balance, the innovation rate dominates the reduction in survival leading to a higher level of product variety over time in high IT firms.

Our results provide empirical support to the conjecture that one pathway by which IT can impact the economics of firms is by enabling greater product variety. This lends further credence to the argument that a significant portion of the value of IT is in creating intangible value. Although prior studies have linked IT to organizational innovation, this research provides evidence that IT is also related to marketplace innovation.

The primary limitation of our work relates to the question of whether trademarks can adequately capture the true level of a firm's product variety. Our measure is consistent with the industry practice of using trademarks to differentiate products. In addition, we are able to validate this measure with a small sample empirical analysis. As discussed in §2, the trademark measure is positively correlated with a subjective assessment of firm variety provided in a recent survey, although these data are, unfortunately, only available for a portion of our sample and represent just a single cross-section. We also find that the trademark count measures are both positively and weakly correlated with measures of industry diversification (Gao 2005).

The advantages and disadvantages of our approach are similar to those encountered when measuring innovative output with patents. In particular, there may be heterogeneity in how firms choose to apply for trademarks as well as heterogeneity in the value of these trademarks. These challenges mirror those that arise in estimating the effect of R&D investment on inventions, for which patent count is used as proxy: "…the patent measure does have several problems, the major ones being that not all new innovations are patented and that patents differ in their economic impact" (Pakes and Griliches 1984, p. 57). A similar concern exists in the business value of IT literature, where there is substantial heterogeneity in the use and level of investment in IT across industry and firms. In our empirical model, we included several control variables to reduce the heterogeneity across firms in the propensity and value of trademark applications. These control variables included firm fixed effects, the degree of competition in each industry, and advertisement expenses. Our log-linear model relies on the fact that trademarks are reflective of the degree of product variety; they are not a perfect measure of the absolute level of a firm's product variety.

Although we have used firm fixed effects and industry-specific variables to try to control for unobserved heterogeneity, given the complexity of the product variety decision, we should caution that our model may, unavoidably, miss some influential factors. For example, Mendelson and Parlaktürk (2008), in an analytical model, showed that both cost efficiency and consumers' perception of quality of products can influence a firm's investment in customization. Goyal and Netessine (2007) examined competition's impact on firms' flexible manufacturing capacity. Recent studies on the business value of IT also confirm that there are considerable cross-firm spillovers (Cheng and Nault 2007) and cross-industry variation (Mittal and Nault 2009). Additionally, institutional forces such as unions may encourage firms to produce products beyond their normal life span.[16] In the future, it will be interesting to examine further how environmental factors moderate the relationship between IT and product variety, and how the impacts of IT vary across industries.

In recent years, new IT applications such as customer relationship management have enabled firms to gain a better understanding of customers' needs. This allows for an increase in the success rate of new product launches. Further, applications such as supply chain management systems and enterprise resource planning (ERP) are becoming more pervasively adopted, making it easier to manage business activities on an integrated digital platform. Because greater variety increases the complexity of day-to-day factory activities (in, for example, labor scheduling, number of invoices, and materials orders; see Fisher et al. 1995), systems that automate operations and integrate production and nonproduction activities can significantly reduce the marginal cost of each activity and can influence a firm's product variety decisions (Dewan et al. 2003). Examination, at a more granular level, of different types of technologies on product variety can generate valuable insights.

This paper examines IT's impact on product variety from a firm's perspective. Innovations in sales technologies, such as the increasing prevalence of online configuration and ordering systems, have also facilitated greater variety (Forza and Salvador 2002, Brynjolfsson et al. 2003, Zhu and Kraemer 2002). Finally, with the rise of "Web 2.0" technologies like blogs, customer reviews, and online communities, companies now have more direct channels to interact with customers. It will be valuable to examine how the changes in channel technologies influence a firm's product updating. We believe that the trademark data may help to advance an understanding of these important issues.

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