Essays on Information Technology and Intangible Capital

by

Adam Saunders

A.B., Economics, Princeton University, 2001

Submitted to the Alfred P. Sloan School of Management
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Abstract

This thesis consists of three essays related to information technology and intangible capital.

The first essay, "Valuing IT-Related Intangible Capital," examines the value of intangible assets in the firm. Using a panel of 130 firms from 2003-2006, we find that intangible assets are correlated with significantly higher market values beyond their cost-based measures. Moreover, we estimate that there is a 30-55% premium in market value for the firms with the highest organizational IT capabilities as compared to those with the lowest organizational IT capabilities.

The second essay, "Has Information Technology Leveled the Competitive Playing Field?" analyzes the relationship between IT and ordinary (non-IT) capital and the competitive dynamics within U.S. industries. Using a panel of industry data from 1998-2005, when an industry becomes more IT intensive, there is more entry and expansion of firms (including entry of new small firms and expansion of large firms from the same and other industries). Yet there is also more turnover of small firms in the industry as well as concentration of the industry into large firms. In contrast, as an industry becomes more ordinary capital-intensive, there is less entry of small firms and fewer establishment openings by large firms; a lower rate of turnover by small firms; and fragmentation of the industry into small firms.

In the third essay, "The Value and Durability of Patents in High-Tech Firms" (co-authored with Erik Brynjolfsson and Lorin Hitt), we use data on publicly traded high-tech companies from 1984-2002 to examine the relationship between the firms' market value and their patent-based intangible assets. We find that high-tech firms with patents that are cited by a wide variety of other patents in different patent classes are worth significantly more than firms with patents that are cited by a narrow range of patents. Patent generality is especially valuable in periods of change, when firms are no longer at the leading edge of innovation in a particular year. In these periods, we find that the value of diverse patents across technology categories is positive but not significant and that generality is comparatively more valuable than diversity.

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Erik Brynjolfsson, Schussel Family Professor of Management, Chair
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My wife Galit has been there with me every day, and I could never have done this without her. This thesis is as much a product of her patience and kindness as it is anything else. I dedicate it to her.

Biographic Note

Adam Saunders is a Lecturer in the Operations and Information Management Department at the Wharton School, University of Pennsylvania. His research measures the value and durability of technology-related intangible assets. He is also studying how IT is changing the competitive playing field among U.S. firms. With Erik Brynjolfsson, he is the co-author of *Wired for Innovation: How Information Technology is Reshaping the Economy* (MIT Press, 2010). His research has been featured in *The Economist*, *Nature*, *Forbes*, *The National Review*, and *CIO Magazine*. He is also the recipient of the Best Paper Award at the International Conference of Information Systems (ICIS) 2010. Before entering MIT, Adam worked at the President's Council of Economic Advisers in Washington, D.C. He holds an A.B. in Economics *summa cum laude* and a Certificate in Finance from Princeton University.

Contents

Chapter 1

Valuing IT-Related Intangible Capital

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As part of an effort to examine the value of intangible assets in the firm, our study creates IT-related intangible asset stocks from firm-level survey data. We also use data on IT-related business practices in order to understand the distribution of IT-related intangibles, and we create asset stocks to value research and development (R&D) and brand. Using a panel of 130 firms over the period 2003-2006, we find that intangible assets are correlated with significantly higher market values beyond their cost-based measures. Moreover, we estimate that there is a 30-55% premium in market value for the firms with the highest organizational IT capabilities (based on a measure of HR practices, management practices, internal IT use, external IT use, and Internet use) as compared to those with the lowest organizational IT capabilities.

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INTRODUCTION

This paper seeks to quantify the value of information technology (IT)-related intangible capital. Although intangible assets are naturally difficult to measure, we utilize a novel approach to doing so by using a market value estimation of a firm's various intangible assets. Our study is the first to create asset stocks based on IT-related intangible spending at the firm level. We also use data on IT-related business practices and management capabilities to analyze where this value is distributed among firms. As part of a broader effort to value intangible assets of the firm, we use market value estimation of research and development (R&D) and brand as well.

Using a balanced panel of annual data of 130 firms from 2003-2006, our results suggest that IT-related intangibles are a significant driver of market value. We recreate the Brynjolfsson, Hitt and Yang (2002) finding that $1 dollar of computer hardware is correlated with more than $10 of market value, suggesting at least $9 of unmeasured intangible assets. We then account for the "other $9" by broadening the definition of IT to include software, and then all IT-intangible spending. The value of $1 of the broadest measure of IT is correlated with close to $1 of market value, its theoretical value. Moreover, we demonstrate that these intangibles are not spread evenly across firms. By replicating an organizational IT capabilities (ITC) variable from Aral and Weill (2007), we estimate that firms with high ITC (1.5 standard deviations and above the mean) are associated with 30-55% greater market value than the firms with low ITC (lower than 1.5 standard deviations below the mean). This effect works in order – high ITC firms are correlated with significantly more value than average ITC firms, which in turn are correlated with significantly more value than low ITC firms. We also find that one dollar of R&D and brand is associated with significantly more than one dollar of value in a market value equation.

The motivation behind our research is that a company's intangible assets are not well captured in government statistics or corporate balance sheets. The Bureau of Economic Analysis (BEA), responsible for publishing the Gross Domestic Product and most other measures of the economy, estimates that U.S. corporations held $12.5 trillion in equipment and structures at the end of 2009.[1] However, it does not estimate the value of intangible assets, such as organizational knowhow, human capital, and brands that are an important source of value for companies today.[2] The value of intangibles is not only missing from government sources; it is also largely absent in corporate balance sheets. Current accounting standards dictate that virtually no intangible investment can be capitalized, that is, treated as an investment and recorded on the balance sheet. One of the few exceptions to this rule is purchased goodwill. When one company buys another, the acquirer adds the net assets of the target to its balance sheet. The additional value of what the acquirer paid over and above the net assets of the target is then added as goodwill to the acquirer's balance sheet. Purchased goodwill, thus, does not include intangibles created outside of mergers and acquisitions. Consider Google, undoubtedly built on a sea of intangible assets and valued at more than $160 billion.[3] The company lists a total of just $40 billion of assets on its balance sheet, $5 billion of which is goodwill. Why is Google valued at $120 billion more than the sum of its assets? Our hypothesis is that while intangibles are mostly invisible on the balance sheet, they are reflected in the market value of companies today.

This does not just apply to companies in the information sector such as Google, but also to traditional "brick-and-mortar" companies as well. We illustrate the difference between the

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[1] Source: BEA Fixed Assets Table 4.1. "Current-Cost Net Stock of Private Nonresidential Fixed Assets by Industry Group and Legal Form of Organization", Line 13.

[2] We note however that the BEA has begun publishing a parallel set of unofficial GDP statistics that treat R&D as an investment rather than as an expense. The BEA plans to fully incorporate R&D as an investment in the core GDP statistics by 2013 (Aizcorbe et al, 2009).

[3] As of August 2010.

market value and balance sheet value of three traditional components of the Dow Jones Industrial Average in Figure 1.

Recent studies have attempted to quantify the size of intangible assets in the U.S. economy using aggregate data and have found vast amounts of uncounted capital. Corrado, Hulten, and Sichel (2005, 2009) estimate that annual business investment in intangibles not included in the U.S. government's official definition of investment could be $1 trillion per year. This uncounted amount is about the same size as the official estimates of annual business investment. They also estimate that the stock of uncounted intangible assets held by business is $3.6 trillion. Nakamura (2001) uses aggregated data on expenditures on intangibles, labor inputs, and corporate operating margins, and estimates that corporate intangible assets in the U.S. economy could be as high as $5 trillion. We seek to contribute to this literature by providing more precise estimates based on firm-level market value equations.

Our main contribution is to be the first to quantify the value of IT-related intangible capital and demonstrate that this value is correlated with firms with more intensive IT practices (e.g. internal IT use, external IT use, and Internet use) and superior management and HR capabilities. Our 2003-2006 dataset provides us with broader and more recent IT estimates than can be found in currently published research by Brynjolfsson, Hitt and Yang (2002) that relies on *Computer Intelligence* data from 1987-1997. In this paper, we build on their framework, that used market value equations to demonstrate that $1 of computer hardware was associated with more than $10 of value, and that this value was accounted for by a set of complementary human resource practices. While IT-related intangible assets were the most plausible explanation for the "other $9" of value, their data was limited to hardware only. With our expanded definition of

IT-related intangibles that measure software, internal IT services, external IT services, and IT-related training, we estimate these values – the "other $9" – directly in a market value equation.

Our study complements and extends recent empirical work that uses financial markets to value IT and intangible capital. Anderson, Banker and Ravindran (2003) use market value equations relating the firm to its book value, earnings, R&D, and Y2K spending and find that the value of a dollar of Y2K spending is correlated with an average of 30-40 dollars of market value (with one estimate being as high as 62 dollars of market value). Their interpretation is that the high values for Y2K spending were likely due to complementary investments in organizational assets as well as improvements to the supply chain as a whole. While this is the most plausible and intuitive explanation, they did not have the data to empirically demonstrate this. Our study uses IT practice and capabilities data directly with intangible IT spending to analyze the size of this intangible value and how it is distributed.

While existing studies have examined the relationship of IT, organizational capital and market value, ours is the first to directly measure and quantify the IT-intangibles in an estimating equation. For instance, Lev and Radhakrishnan (2005) use the firm's sales, general, and administrative (SG&A) expenses as a proxy for organizational capital in a sample of publicly traded companies. They find this measure of organizational capital is significant in explaining a firm's sales, and that this measure is also highly correlated with the firm's spending on IT. Together, they explain market value beyond traditional measures such as book value and growth potential. Their results, while quite powerful, rely purely on spending data, and our work builds on their findings as we use organizational practice data as well as specific IT-intangibles spending to estimate IT-related organizational capital.

We see our findings as complementary to the observation that IT investments are significantly riskier than non-IT investments (Dewan, Shi and Gurbaxani, 2007). IT capabilities are neither easy to create nor copy because they involve a *system* of practices. While copying any one piece might be straightforward, an organizational system as a whole is difficult to duplicate (Brynjolfsson, Renshaw and Van Alstyne 1997; Milgrom and Roberts 1990, 1995; Porter 1996). Our finding that the highest ITC firms are correlated with 30-55% more value than the low ITC firms fits perfectly in this framework. The rewards are higher for the firms that have built an interlocking system of complementary IT capabilities because these investments involved significant risk.

Our paper uses estimated values of R&D and brand directly in a market value equation, complementing other approaches in the literature that value these intangibles using event studies, production functions, and discounted *ex-post* future returns. Hand (2003), using a net present value (NPV) profitability model, finds that the NPV of R&D and brand is significantly positive and that the firms that were the largest spenders in R&D and advertising were the ones with the highest returns to those assets. Lev (2004) notes that the companies with the highest amounts of R&D capital had the highest risk-adjusted returns between 1983 and 2000, implying that "R&D-intensive companies were systematically underpriced by the market," (Lev 2004, p.110). Barth et al. (1998) finds that brand value estimates are a significant and positive predictor of share prices and future returns. Using a production function framework, Seethamraju (2003) estimates the value of trademarks, and finds this estimated value is reflected in share prices. These approaches demonstrate that despite their absence from the balance sheet, R&D and advertising are highly valuable investments and are subject to increasing returns to scale. Using the market value equation framework, our paper is another lens to quantify the value of these intangibles.

The remainder of our paper is organized as follows. The next section outlines our conceptual framework and is then followed by our econometric model. We then describe the data used in this study, follow with our results, and conclude with a summary and implications for future research.

Conceptual Framework

We begin with the simple, yet elegant principle that the total value of financial claims on the firm should be equal to the sum of the firm's assets (Baily, 1981; Hall 2000, 2001). Our underlying assumption is that financial markets provide an important way to value intangible assets beyond the balance sheet and other input metrics. We model the value of financial claims against the firm, *MV*, as the sum of each of its *n* assets, *A* (based on the model in Brynjolfsson, Hitt and Yang 2002, pp.150-151):

$$MV = \sum_{i=1}^{n} A_i \tag{1}$$

In other words, "If all assets can be documented and no adjustment costs are incurred in making them fully productive, buying a firm is equivalent to buying a collection of separate assets. Thus the market value of a firm is simply equal to the current stock of its capital assets," (*ibid*).

As noted earlier, while Google is valued at approximately $160 billion, the company lists $40 billion in total assets on its balance sheet, of which only $5 billion is intangible. While we can measure physical assets for publicly traded companies because of the accounting regulations that require their inclusion in balance sheets, measuring intangible assets poses significant challenges: With the exception of goodwill, they are virtually invisible on corporate balance sheets.

One of the key contributions of this paper is to be the first to create several types of intangible asset stocks and measure them directly in an empirical estimation of (1). That is, rather than *assume* that the residual of the firm's market value above and beyond the firm's book value is due entirely to intangibles, we construct measures for each intangible asset to estimate directly. Put another way, we don't begin with the assumption that the other $120 billion of Google's market value is the sum of its intangible assets. Rather, in our approach, we estimate how much each type of asset – physical, financial, and intangible – contributes to the entire $160 billion.

Our null hypothesis is that a dollar's worth of an asset should contribute to one dollar of market value. To test this, we construct three types of intangible asset stocks based on aggregated historical spending to include in the market value equation: IT-intangibles, advertising, and R&D. In the absence of these assets from the corporate balance sheet, we estimate the relationship of our constructed measures and market value.

Even with an ideal dataset that could accurately measure both the tangible and intangible assets of the firm, we would need to control for factors such as industry and year in an estimation of (1). In any given year, the market value of two firms with identical quantities of assets that operate in different industries will differ because of differences in industry growth rates, or regulation, for example. There are also time-varying unobserved factors, such as excessive optimism or pessimism on the part of investors, that necessitates controlling for year in an estimation of (1).

Econometric Model

To relate the market value of the firm to its various assets, we use the following estimating equation:

$$MV_{it} = \beta_0 + \beta_1 K_{it} + \beta_2 F_{it} + \beta_3 IT_{it} + \beta_4 R_{it} + \beta_5 B_{it} + controls + \varepsilon_{it} \quad (2)$$

The value of all financial claims on the firm (equity plus liabilities) are placed on the left-hand side and are represented by *MV*. (Subscripts *i* and *t* represent firm *i* in year *t*.) We list various categories of assets on the right side of the equation. The first is physical, non-IT (ordinary) capital, *K*. This includes non-IT equipment, structures, land, and inventories. Next is financial assets, *F*, which represents total balance assets minus physical capital. This includes receivables, cash, and other accounting assets such as goodwill. The next term is *IT*, which represents information technology assets. We will use three different measures of IT in our analysis. The first measure includes purchased hardware only, the second includes capitalized hardware and software, and the third, broadest measure of IT includes all hardware and software, internal IT services, external IT services, and IT-related training. The term *R* represents R&D assets, and *B* represents advertising spending converted into an asset. We include controls for year and industry, as well as dummy variables for firms that have zero R&D or firms for which we impute advertising expenditures.

Given that our data is in panel form, we estimate equation (2) using Generalized Least Squares (GLS) to correct for potential serial correlation of the error terms and heteroskedasticity. Since one of our goals is estimating the distribution of IT-intangible capital between the firms in sample, we do not use fixed effects or first-differencing as this would sweep away the effects we are looking to measure. One of the principle assumptions in random effects estimation is that the firm effect is uncorrelated with all of the explanatory variables. However, as Hall, Jaffe and

Trajtenberg (2005) note, this assumption would be inappropriate in estimating the value of R&D: "R&D tends to change slowly over time, a firm's R&D intensity is highly correlated with its individual effect; in fact, it is an important component of what creates differences across firms, so removing these effects would entail an overcorrection, " (p.26). This can well apply to IT-intangible spending as well. In addition, since the time period in our panel is relatively short, if we use fixed effects or first differencing with Ordinary Least Squares (OLS), any measurement error in the slowly changing right-hand side variables is going to significantly bias the coefficients downward (Griliches and Hausman, 1986).

To estimate the value of a dollar of ordinary capital, *K*, we adjust net property, plant and equipment (PP&E), listed in net historical-cost dollars (based on the year the asset was purchased) into a replacement cost, or current-cost measure (how much it would cost to purchase the asset in that year). We use the unadjusted value of financial assets listed on the balance sheet and assume this approximates a current-cost measure. To measure *IT*, *R*, and *B*, we use the perpetual inventory method (PIM) to aggregate historical spending and create asset stock values based on depreciation rates and price deflators from the BEA or BLS. If none exist (such as depreciation rates for advertising), we use reasonable values based on the prevailing practice in the literature.

Our null hypothesis is $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 1$. If any of these coefficients are greater than 1, then it means that firms, on average, are reaping greater value than the replacement costs of those assets. This does not mean that there is a "free lunch" in the markets, especially when it comes to intangible assets. If intangible assets carry more unpredictable upside payoffs, it is reasonable to test $\beta_3, \beta_4, \beta_5 = 1$ against the alternative hypothesis that they are greater than 1. This extra value could represent a market premium for the additional risk in those assets.

Another reason the coefficient can be above 1 is because of omitted variable bias. Brynjolfsson, Hitt and Yang (2002) found \$1 dollar of computer hardware was correlated with more than \$10 of market value. They reasoned that this was due to omitted IT-intangible capital. When they included a measure of organizational practices interacted with hardware, the coefficient on hardware alone fell significantly. With three different measures of IT ranging from hardware only to a broad measure encompassing all IT spending on intangibles, we have direct data to measure the "other \$9" in an estimating equation.

When it comes to intangible assets, cost-based measures may not be enough to describe their value. That is, if two manufacturing firms spend \$20 million on bulldozers, it is reasonable to expect that the inherent replacement *value* of this equipment is not firm specific. Yet this reasoning does not apply well to intangibles. If two firms spend \$20 million on an Enterprise Resource Planning (ERP) system, it is reasonable to expect that the value of that system *is* going to be firm specific. A number of recent papers have shown that complementary business practices are necessary to get the full value from IT (Bartel, Ichniowski, and Shaw 2007; Bloom, Sadun and Van Reenen, 2007; Bresnahan, Brynjolfsson and Hitt 2002; Brynjolfsson and Hitt 2003; Brynjolfsson, Hitt and Yang, 2002; Crespi, Criscuolo and Haskel 2007; Dedrick, Gurbaxani, and Kraemer, 2003; McKinsey Global Institute, 2001, Pilat 2004).

To examine the distribution of IT-intangibles, we construct a variable to capture management capabilities and organizational IT practices. This is based on the measure created by Aral and Weill (2007) they termed organizational IT capabilities (ITC). We use this variable to test whether most of the value from IT-related intangibles is concentrated in the firms with high ITC.

We construct ITC as a standardized (mean 0, variance 1) variable. We then create four dummy variables based on the firm's ITC score. If ITC is less than 1.5 standard deviations from the sample mean, then ITC_F = 1, otherwise, it is equal to 0. If ITC is between -1.5 and -0.5 standard deviations from the sample mean, ITC_D = 1, otherwise it is 0. The variable ITC_B =1 if ITC is 0.5 to 1.5 standard deviations above the sample mean, 0 otherwise, and ITC_A =1 if ITC is greater than 1.5 standard deviations from the sample mean, and 0 otherwise. The baseline group is composed of firms for which ITC is between -0.5 and 0.5 standard deviations from the sample mean, which we call ITC_C. (One can think of the F, D, C, B and A levels of ITC similar to an academic letter-grade system). Using this set of dummy variables, we construct the following estimating equation:

$$\begin{aligned} MV_{it} &= \beta_0 + \beta_1 K_{it} + \beta_2 F_{it} + \beta_3 IT_{it} + \beta_4 R_{it} + \beta_5 B_{it} \\ &+ \beta_6 ITC\_F + \beta_7 ITC\_D + \beta_8 ITC\_B + \beta_9 ITC\_A \\ &+ \beta_{10} IT_{it} * ITC\_F + \beta_{11} IT_{it} * ITC\_D + \beta_{12} IT_{it} * ITC\_B + \beta_{13} IT_{it} * ITC\_A + controls + \varepsilon_{it} \end{aligned} \tag{3}$$

For the baseline group of ITC_C firms, the total contribution of *IT* dollars to market value would be $\beta_3 \cdot IT$ dollars. For an ITC_F firm, the total contribution of *IT* dollars to market value would be $(\beta_3 + \beta_{10}) \cdot IT + \beta_6$ dollars. For an ITC_A firm, the contribution of *IT* dollars to market value would be $(\beta_3 + \beta_{13}) \cdot IT + \beta_9$ dollars. Our null hypothesis is that the eight coefficients β_6 through β_{13} are equal to zero.

DATA

Our data consists of a balanced panel of 130 publicly traded U.S. companies, representing a broad cross-section of industries. With annual data from 2003-2006, we have a total of 520 observations. We construct our sample by starting with firms that are publicly traded and participated in the Social and Economic Explorations of IT (SeeIT) survey, a two year effort by the MIT Sloan School to poll companies about IT spending and technology usage. We match those firms to *Compustat*, and eliminate firms with missing market value, total assets, or ordinary capital. We drop a small handful of firms with implausibly high computer hardware estimates (as compared to their measures of property, plant and equipment in *Compustat*).[4] We also eliminate companies headquartered outside the United States, to eliminate confounding effects coming from companies subject to different tax laws, markets, culture or regulation. To create a balanced panel, we keep firms that have complete data in every year from 2003 through 2006. All of the firm-level data is constructed on a fiscal year-end basis. We display the sample summary statistics in Table 1.

We also exclude IT-producers, financial, mining, and oil companies. IT-producers face different input prices for computer hardware and software than the rest of the economy (since such firms use the IT they produce themselves). We drop firms with primary industry codes in Computers and Semiconductors (NAICS 334); Software publishing (NAICS 5112); Information and Data Processing Services (NAICS 514) and Computer System Design and Related Services (NAICS 5415). We also exclude financial corporations (NAICS 52) because they are fundamentally different from other firms in the economy, and have such high levels of financial assets that it may affect our estimate for the coefficient of F. Mining and oil companies (NAICS 21, 324) hold significant assets that fluctuate with the market price of the underlying commodities, yet such changes are not reflected on the book value of assets on the balance sheet.

[4] Such as when the estimate for hardware is greater than all of property, plant and equipment, or when our estimate for hardware is greater than all of equipment (meaning that non-IT equipment would be zero or negative).

Because of the large potential changes to the left-side variable (market value) without resultant changes to the right-side variables, we exclude such firms.

Market Value

We define market value as the sum of all financial claims on the firm at the end of each fiscal year, as shown in equation (4):

$$MV = PSTK + (PRCC\_F * CSHO) + LT + ADJ \tag{4}$$

MV, or market value, is the sum of four separate terms. The first is the value of preferred stock (*PSTK*), the second is the price of common stock at the end of the fiscal year (*PRCC_F*) times the number of outstanding shares of common stock (*CSHO*), and the third is total liabilities (*LT*). The last term is an adjustment to the face value of long-term debt (*DLTT*), which reflects the additional premium (or discount) of the market value of bonds to the face value of bonds. If the market value of bonds is equal to the face value, this term is equal to 0.

For data to adjust long-term debt, we start with the *Mergent Fixed Income Securities Database*, with data on approximately 180,000 corporate bond issues. We extract the unique CUSIP identifier and issue information for each bond. We match this to the *Trade Reporting and Compliance Engine (TRACE)* database, a product of the Financial Industry Regulatory Authority (FINRA). The TRACE database represents more than 99 percent of U.S. corporate bond market activity of 30,000 issuers. From January 2003 through December 2006, the database contained more than 18 million trades. For each bond, we keep the last recorded price for the close of the fiscal year. We aggregate the face and market values of all outstanding bonds for each company, and match this to our sample. Finally, we use the ratio of the market value to the face value of a company's outstanding bonds and apply it to the face value of the company's long-term debt.

IT Capital

The IT spending and practice data comes from the SeeIT survey. The survey was conducted using telephone interviews in 2005 and 2006 with a single point of contact in each company. The data covers spending from 2003-2006, and IT practices in 2005 and 2006. Approximately 600 companies participated in the survey and about half of them were publicly traded. The majority of respondents were CIOs, in IT finance functions, or in IT project management functions. The questions included the amount of computer capital in the firm, as well as annual spending on hardware, prepackaged software, external IT services (e.g., business process consulting, integration services), internal IT services (e.g. writing software, design, maintenance, and administration), and IT-related training. (The IT practice questions are used to construct an IT capabilities variable as described in Table 5.)

The firm-level IT spending data is summarized in Table 2. On average, each firm in our sample spends $258.5 million per year on IT, of which $32.4 million, or about 12.5% is for hardware. We convert this spending into three different measures of IT assets in our analysis, moving from narrow to broad:

1. Purchased Hardware: This replicates the measure from Brynjolfsson, Hitt and Yang (2002), who use hardware owned by the firm (whether or not it is capitalized).

2. Capitalized Hardware and Software: This represents what would be on the balance sheet of the company. (Note this does not include the uncapitalized purchases of hardware that were in the first measure.)

3. All IT: Our broadest measure of IT is capitalized, uncapitalized purchases, and leases of hardware and software, as well as spending on other internal IT services, external IT services, and training that we convert into asset stocks.

To create the three measures, we estimate what percentage of IT spending in each category of Table 2 is capitalized. We use an industry-level Census survey to estimate the extent that firms capitalize IT.[5] The *Annual Capital Expenditure Survey* (ACES) contains the *Information and Communication Technology Supplement*, categorizing hardware and software spending into capitalized and uncapitalized amounts for each of the 20 major NAICS sectors.

We match the industry-level capitalization ratios to our firm-level data and list the summary statistics in Table 3. In our sample, firms capitalized an average of 64.0% of their hardware spending from 2003-2006, and this ranged from 51.2% to 84.7%. For software, while an average of 53.1% of software spending was capitalized, it ranged between 26.5% and 68.7%.

In Table 4, we list our estimates of IT assets for the sample in 2003-2006. For instance, the average firm held $34.2 million in purchased, capitalized hardware. We also estimate that the average firm held another $10.8 million in purchased hardware that was not capitalized. This is not listed separately in Table 4, rather we list the total of all uncapitalized hardware ($21.5 million) of which we estimate $10.8 million is purchased and $10.7 million is leased. Therefore, our first measure of IT, purchased hardware, averaged $45.0 million ($34.2 + $10.8 million) per firm during the sample period. Our second measure of IT, capitalized hardware and software, averaged $202.9 million per firm. Our third and broadest measure of IT (which includes IT services and training) averaged $562.9 million per firm.

To construct each of the IT assets listed in Table 4, we used the following methods:

[5] We use an industry-level survey because we cannot observe firm decisions to capitalize IT in each year.

Hardware: We begin with total hardware spending as reported by the firm (Table 2, Line 1).[6] This is an unadjusted figure from the year in which the hardware was purchased. We convert each of these flows into a constant-dollar (2000) measure using the industry-specific price deflator for computers and peripherals from the BLS. We divide each year's spending into three categories, using the industry-level data from the ACES: Capitalized purchases (Table 3, line 2), uncapitalized purchases (line 3) and leases (line 4). We use a three-year service life for hardware and assume these investments are made halfway through the year (as is the practice of the BEA and BLS). For example, the stock of hardware in constant dollars at the end of 2006 is the sum of each constant-dollar flow from 2004, 2005, and 2006, depreciated at an average of 30.8% per year.[7] The constant-dollar asset stock measure is then converted back into a current-dollar, or replacement cost measure, using the price deflator for computers and peripherals in 2006. This is repeated to get current-dollar estimates from 2003-2006.

Because we use three years of flow data to calculate each year's worth of computer assets, and our spending data covers 2003-2006, the 2003 and 2004 asset stocks include imputed flow data (from 2001 and 2002). To impute this earlier hardware spending, we start with the firm's reported spending in 2003, and apply the BLS industry-level growth rate of hardware from 2001 and 2002 to create historical values of hardware spending.

Prepackaged Software: Similar to hardware, we convert all flow data reported as prepackaged software by the firm into a constant dollar measure, and use price deflators and

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[6] Although the SeeIT survey asked firms to report their stock of hardware, we create stocks from firm spending rather than use reported hardware stocks because we are concerned whether the asset stock measures reported by the firm truly reflect the *replacement* cost and not the *historical* cost. To be consistent between firms and with the other asset stocks we calculate, we concluded it was more reliable to use reported spending totals from the years in which the assets were purchased and apply appropriate price deflators and depreciation rates to create the asset stocks.

[7] The rate of depreciation for computers and peripherals from the BLS is also industry-specific and depends on the composition of hardware in each industry.

depreciation rates from the BLS. We use the industry-level capitalization ratios from the ACES data to divide the spending into capitalized purchases, uncapitalized purchases, and leases. We also use a three-year service life. We impute the 2001 and 2002 spending on prepackaged software from the 2003 reported spending and the 2001 and 2002 industry-level growth rates of prepackaged software investment from the BLS. The constant-dollar estimates are then converted back into current-dollar estimates using the BLS price deflator for prepackaged software.[8]

Custom software: As opposed to prepackaged software, which is ready to use off the shelf, custom software "is tailored to the specifications of a business enterprise or government unit" (BEA 2000, p.3). It includes expenses for programs as well as payments to freelance programmers or outside organizations to develop the software.[9]

We begin with the firm's reported spending on External IT services and allocate it to create two asset stocks: custom software, and miscellaneous External IT services. To identify how to allocate this spending, we use the *Service Annual Survey* conducted by the Census Bureau. We proxy for the industry providing all External IT services as NAICS industry 5415, Computer System Design and Related Services. Revenue from this industry was $188.3 billion

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[8] For all asset stock calculations below, we do the following: 1) Use appropriate price deflators to convert nominal flows into constant dollar flows; 2) Use the appropriate depreciation rates and service lives to create constant dollar asset stocks; and 3) Convert each year's constant-dollar asset stocks into current-dollar asset stocks using that year's price deflator.

[9] The full definition from BEA (2000, pp. 3-4) is: "Custom software is software tailored to the specifications of a business enterprise or government unit. It may include new computer programs as well as programs incorporating preexisting or standardized modules. Expenditures for custom software include those for the development (analysis, design, and programming) of software tailored to the business enterprise's or government unit's specifications. The expenditures include payments to free-lance computer software writers and to consulting organizations and individuals, who are not employees, who perform programming and systems analysis to support the development of software. It also includes expenditures on tailored software that is modified by providers of software or computerized equipment. The large majority of producers of custom software were previously classified in SIC 7371 (computer programming services) and are now classified in NAICS 541511 (custom computer programming services)."

in 2006. The industry we proxy as custom software is NAICS 541511, Custom Computer Programming Services, and is a subset of NAICS 5415. Revenue in NAICS 541511 was $64.3 billion in 2006. Thus, our estimated ratio of custom software spending to all External IT services spending was roughly 34% (64.3/188.3) in 2006. We do this calculation in other years and find this ratio to be steady from 2003-2006.

The 34% of External IT services spending that is allocated to custom software is further divided into capitalized and uncapitalized portions. We use BLS depreciation rates and price deflators for custom software, and use a five-year service life. We impute firm-level spending for 1999-2002 from the BLS industry-level growth rates of custom software, applied to the 2003 firm-level value of custom software investment.

Own-Account Software: The definition of own-account software "is in-house expenditures for new or significantly-enhanced software created by business enterprises or government units for their own use," (BEA 2000, p.4).[10] We begin with the firm's reported spending on Internal IT services and allocate 50% of this to own-account software and the other 50% towards maintenance and administration, as is the current practice of the BEA (BEA 2000). The 50% that is not part of own-account software is allocated to an asset stock we call miscellaneous Internal IT services and is described further detail below.

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[10] The full definition of own-account software from BEA (2000, p.4) is: "Own-account software consists of in-house expenditures for new or significantly-enhanced software created by business enterprises or government units for their own use. These expenditures include: Wages, salaries, and related compensation (such as contributions to pensions and for FICA), materials and supplies consumed, and indirect costs. The indirect costs include depreciation of plant and equipment, utilities, travel, property and other taxes, maintenance and repair of plant and equipment, and overhead--including personnel, accounting, and procurement. The expenditures are made for analysis, design, programming, and testing of software and may be made by any industry....Software-related expenditures treated as investment exclude maintenance and repair expenditures on existing software, including expenditures to fix so-called "Y2K" problems. In addition, in-house expenditures on software that is to be embedded in computers and other equipment that is to be sold are excluded from software investment in order to avoid double-counting."

For the part that is own-account software, we divide this into capitalized and uncapitalized portions according to the industry-level ratios in the ACES data. We use the depreciation rates and price deflators from the BLS, and use a 5-year service life. We impute firm-level spending for 1999-2002 from the BLS industry-level growth rates of own-account software, applied to the 2003 firm-level value of own-account software investment.

Miscellaneous External IT Services

This asset stock is created from the 66% of External IT Services spending that is not allocated to custom software, which includes activities such as business process consulting and integration services. This asset stock is treated as uncapitalized. There are no price deflators or depreciation rates for this capital available from the BLS, thus we use the closest available substitutes. We use a 37.2% annual rate depreciation, which is the average of R&D and advertising (following the methodology for firm-specific resources in Corrado, Hulten, and Sichel 2005, 2009). The price deflator we use is the BEA gross output deflator for NAICS 541512, Computer Systems Design Services. We use a 5-year service life, and impute firm-level spending for 1999-2002 from the BLS industry-level growth rates of custom software, applied to the 2003 firm-level value of miscellaneous External IT services spending.

Miscellaneous Internal IT Services: This asset stock is created from the 50% of Internal IT Services spending that is not allocated to own-account software, which includes activities such as maintenance and administration. This asset stock is treated as uncapitalized. We use the same depreciation rate as we do for Miscellaneous External IT Services (37.2%), and also use the gross output deflator for NAICS 541512. We use a 5-year service life, and impute firm-level spending for 1999-2002 from the BLS industry-level growth rates of own-account software, applied to the 2003 firm-level value of miscellaneous Internal IT services spending.

Training: We use the spending reported by the firm for IT-related training and convert it to an uncapitalized asset stock. We use the same depreciation rate (37.2%) as we do for the other intangible asset stocks we created (Miscellaneous Internal Services and Miscellaneous External IT Services), and the same gross output deflator (NAICS 541512) to convert the flows into constant-dollar measures. We also use a 5-year service life, and impute firm-level spending for 1999-2002 from the BLS industry-level growth rates of custom software, applied to the 2003 firm-level value of IT training.

Research and Development (R&D) Capital

We begin with R&D as reported by the firm (*Compustat* mnemonic XRD) and apply BEA price deflators and depreciation rates to create an R&D asset stock. The R&D depreciation rate for firms in Transportation and Warehousing (NAICS 48-49) is 18%, for Chemicals (NAICS 325) it is 11%, and for all other firms it is 15%.[11] We use a 20-year service life for R&D. Approximately half the firms in our sample report nonzero values of R&D. Since U.S. firms are required to report R&D spending if it exceeds 1% of sales (Zhao 2002), we assume zero R&D spending for firms that do not report R&D. We create a dummy variable equal to one if a firm does not report R&D and use it in all of our estimating equations. For firms that generally report R&D, but have some values missing, we impute the missing values by taking the R&D/sales ratio for the trailing or leading five years and applying it to the sales in the year(s) of missing R&D. By current accounting practice, no R&D spending is capitalized.

Brand Capital

We start with advertising spending data reported by the firm (*Compustat* mnemonic XAD) where possible. Approximately 50 percent of firms in our sample report advertising

[11] The BEA rate for R&D depreciation in the computers and electronics industry is 16.5%, but we do not use IT-producing firms in our sample.

expenditures. Advertising costs are typically disclosed in financial reports when material, and so we are reasonably confident that this covers the firms that spend significant amounts on advertising. However, for the firms that do not report advertising, we use a database maintained by Kantar Media called *Ad$pender*, that reports estimated advertising costs for 95% of firms covered by *Compustat*. For the handful of firms (less than 10 in our sample) that we could not get data from either source, we use industry-level advertising to sales ratios from *Schonfeld & Associates*. We construct the asset stock of advertising using a 60% deprecation rate (following Corrado, Hulten and Sichel 2005, 2009). We use the producer price index (PPI) for advertising agencies as a price deflator and use an 8-year service life. By current accounting practice, advertising in not capitalized.

Ordinary Capital

We define ordinary capital as equipment, structures, land and inventories minus capitalized IT (which is either hardware only, or hardware and software depending on the estimating equation).[12] In *Compustat*, this is net property, plant and equipment (mnemonic PPENT) plus inventories (mnemonic INVT), minus our measure of capitalized IT. We disaggregate the net historical cost, or book value measure of property, plant, and equipment into current-cost measures of non-IT equipment, structures, and land for each firm. This is a somewhat involved procedure and is described in further detail in Appendix B. This adjustment was made in an attempt to keep all assets in the estimating equations in current-cost, rather than historical-cost values.[13]

[12] This is to be consistent with the BLS definition of capital. The BLS has a fifth category, rental residential capital, which only applies to the Real Estate industry (NAICS 531). Further detail can be found in BLS (1983, Appendix C).

[13] At the end of 2006, the current-cost value of structures held by businesses was $6,910.5 billion, whereas the net historical cost, or book value of these same structures was $3,522.9 billion. Source: BEA Fixed Assets Table 4.1, "Current-Cost Net Stock of Private Nonresidential Fixed Assets by Industry Group and Legal Form of

Other Assets

We define other assets as total balance sheet assets (*Compustat* mnemonic AT) minus net property, plant and equipment (PPENT) and inventory (INVT). This includes financial assets such as accounts receivable, cash, other liquid assets, and any other accounting assets intangibles on the balance sheet.

IT Capabilities (ITC)

The ITC variable is based on Aral and Weill (2007). It is the sum of five components, which comprise management capability, human resource capability, IT usage in communications internally and externally, and Internet usage.[14] Each component is constructed from the sum of several questions on a 1-5 scale that were in the 2005 and 2006 SeeIT surveys.[15] To reduce measurement error, we average both measures and give each firm a single value for the sample period. We standardize each of the five component sums to mean 0, variance 1 variables. We than add those five components, and restandardize that sum to create the mean 0, variance 1 variable we call ITC. We list the components and summary statistics of ITC in Table 5, and the distribution of ITC (from ITC_F through ITC_A) in Table 6.

Control Variables

We create sector control variables, and in order to have at least 20 observations for each sector dummy, we aggregate similar NAICS sectors. We list the sector classifications in Table 7.

Organization," Line 15, and BEA Fixed Assets Table 4.3, "Historical-Cost Net Stock of Private Nonresidential Fixed Assets by Industry Group and Legal Form of Organization", Line 15.

[14] We do not have enough response data to create the sixth component in Aral and Weill (2007), which measures the degree of digitization in purchase and sales.

[15] A much more detailed description of the questions can be found in Aral and Weill (2007).

RESULTS

Our results are as follows: With our 2003-2006 dataset, we are able to recreate the Brynjolfsson, Hitt and Yang (2002) finding that $1 dollar of computer hardware is correlated with more than $10 of value. We then account for the "other $9" by broadening the definition of IT to include software, and then all IT intangible spending. The value of $1 of the broadest measure of IT is correlated with close to $1, its theoretical value.

However, our results suggest that this value is not spread evenly throughout the sample. Rather, it is positively correlated with the firms with the highest capabilities (such as the ITC_A firms) and is negatively correlated with the firms without such capabilities (such as the ITC_F firms). The difference in market value between these groups is striking: Holding fixed all physical as well as intangible assets of the firm, we estimate a 30-55% value premium to the ITC_A firms over the ITC_F firms. This finding holds up to alternative specifications as well as several robustness checks. The estimated premium of being an ITC_A firm is consistent with the observation that IT investments are riskier than ordinary investments (Dewan, Shi, and Gurbaxani, 2003) and thus, the firms that do IT well are rewarded handsomely by the market.

We also estimate $1 of R&D and brand capital is correlated with more than $1 of value, whereas we do not find the same premiums to physical or financial capital. This further suggests that intangible assets, rather than physical assets, are what differentiate firms.

Because the market value equations use the *replacement* cost of computers (the cost to replace the stock of computers in the dollars of that year), and not *historical* cost (the cost of the computers in the year in which they were purchased), the market value of $1 of replacement-cost computers, in theory, should be no different from year to year. This will allow us to compare our results directly to Brynjolfsson, Hitt and Yang (2002). From 1987-2006, the stock of hardware held by businesses in the United States grew 215%, from $76 billion to more than $161 billion (Figure 2). However, this barely outpaced the Consumer Price Index (CPI), which grew 175% during the same period. The story is very different when we take into account the quality changes to computing: U.S. businesses held 32 times as much computing power at the end of 2006 as they did in 1987.[16] However, even though 20 years of technical change have produced computers of stunningly different quality, the market value of $1 of new 1987 computers in 1987 should be no different than the market value of $1 of new 2006 computers in 2006.

When we examine investments in IT made by businesses in the United States, we find that the ratio of intangible-IT spending to hardware spending in our sample is similar to that of the economy as a whole. In our sample, we compute $6.98 in intangible IT for every $1 of hardware spending from 2003-2006 (Table 2). For the U.S. economy in 2003-2006, for every $1 dollar of hardware investment, businesses spent $6.13 in software, internal IT services and external IT services (including training). Intangible investments in IT have grown significantly in the United States from 1990-2006, from $95 billion in 1990 to more than $450 billion in 2006 (shown in Figure 3).[17]

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[16] Source: Bureau of Economic Analysis, Fixed Assets Table 2.2. "Chain-Type Quantity Indexes for Net Stock of Private Fixed Assets, Equipment and Software, and Structures by Type," Line 5. The value of the quantity index was 3.507 in 1987, and 113.598 in 2006 (with 2005 as the base year, equal to 100).

[17] Source: Hardware and Software (prepackaged, custom, and own-account) investment from BEA NIPA Table 5.3.5, "Private Fixed Investment by Type," Lines 11 and 12. IT services consist of Internal IT services and External IT services. IT training is included in IT services. Since the BEA allocates 50% of all Internal IT spending for own-account software, we create a category for Internal IT Services as equal to spending on own-account software. Spending on External IT services from the *Service Annual Survey*. From 1998-2006, we use revenue in NAICS industry 5415 (Computer Systems Design and Related Services) minus 541511 (Custom Computer Programming Services), since NAICS 541511 is allocated for custom software. For 1990-1997, we use the revenue from SIC industries 7373, 7376, and 7379 as this most closely matches the industries from NAICS 5415 excluding 541511. We further adjust the SIC estimates to match the NAICS definitions by multiplying the SIC estimates by the ratio of the NAICS to SIC revenue in these industries in 1998, the only year in which data in both formats is available. We begin with 1990, the first year with data available from SIC codes 7373, 7376, and 7379 in the *Service Annual Survey*.

In Table 8, we use market value estimation of equation (2) for all three of our measures of IT, moving from the narrowest measure (purchased hardware) to including all IT-related intangibles. Column 1 is an attempt to replicate the results from Brynjolfsson, Hitt and Yang (2002). We see that one dollar of computer capital, defined as hardware only, is correlated with about \$11 of value, significantly above its theoretical value of \$1. In contrast, a dollar of ordinary capital and other assets are correlated with close to \$1. These results are similar to the results in Brynjolfsson, Hitt and Yang (2002, p.160).[18] They did not maintain that that hardware itself is worth more than \$10, (and neither do we), but that this hardware is correlated with unmeasured intangibles. We examine this hypothesis in Columns 3-6.

Although \$1 of our broadest measure of IT is correlated with close to \$1 of value *on average*, our results suggest that high ITC firms account for a disproportionate share of the value IT-intangibles. In Table 9, Column 3, we estimate that holding all assets fixed, the difference in value between the ITC_A and the ITC_F firms is 3,999 – (-4,925) million, or \$8.9 billion. We estimate the difference in value between the ITC_F firms and the ITC_B firms is about \$7.6 billion. The same is true when using capitalized IT in Column 1. These differences are statistically significant at the 1% level, and are practically significant as well. Since the average market value of the firms in our sample is \$31.1 billion, an \$8.9 billion difference is almost a 30% premium in market value for the companies with the highest IT capabilities over the companies with the lowest IT capabilities.

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[18] Our results from OLS estimation (not shown here) are also similar to Brynjolfsson, Hitt and Yang (2002) and are qualitatively similar to our GLS results. One dollar of computer capital is correlated with more than \$10 of value, and a dollar of ordinary capital and other assets are each correlated with close to \$1 of value. When we broaden the definition of IT, we estimate coefficients closer to 1. One dollar of advertising and R&D are associated with significantly more than \$1 of value, and ITC can predict significant differences in market value.

Our results suggest that organizational IT practices are highly complementary to investments in IT. That is, \$1 dollar of IT capital in an ITC_A firm is correlated with significantly higher value than \$1 of IT capital in an ITC_C or ITC_F firm. This is shown in Table 9, Column 4, with the full set of interaction terms for IT and ITC. For an ITC_A firm with the sample average of the broadest measure of IT assets (\$562.9 million), the total estimated effect of IT on market value is (25.81+0.01)*562.9 – 2,570 million, equal to \$12.0 billion. However, for an ITC_F firm with the same amount of IT, the total estimated effect of IT on market value is (5.55+0.01)*562.9 – 8,300 million, equal to -\$5.2 billion. In other words, each dollar of IT is correlated with *negative* nine dollars in market value. The difference between these two groups is \$17.2 billion, significant at the 1% level, and very large in a practical sense – amounting to more than 55% of the average market value of the firms in the sample. The estimated difference between the top and bottom performers is similarly striking if we use capitalized IT instead (Column 2).

There isn't just a significant difference in value that can be explained by the extreme ends of the distribution of ITC. We also estimate significant differences in value between the average (ITC_C) firms and the ITC_A and ITC_F firms. In Table 9, Column 4, \$562.9 million of the broadest measure of IT in the ITC_C firms is estimated to be valued at 0.01*562.9, or \$5.6 million, and this is not statistically different from 0. However, this is \$5.2 billion more than that ITC_F firms, and \$12.0 billion less than the ITC_A firms. Both of these differences are statistically significant at the 1% level.

In the analyses in Tables 8 and 9, we reject the null hypothesis that the coefficients of R&D and brand are equal to 1 against the alternative that they are greater than 1 at the 5% level of significance. We were surprised by the large value for brand, and upon further analysis, found a single, large consumer products company drove a substantial part of this value. If we drop this company from the sample and rerun the analyses in Tables 8 and 9 (not shown), we find that the coefficients of the other variables remain virtually unchanged but the coefficient for brand drops to below 5 in Table 8, and is approximately 3 in Table 9. This suggests that when it comes to brand, certain industries (such as consumer products) are disproportionately important. This observation fits with our findings that most of the IT-intangibles appear to be concentrated in a small number of firms. The same is likely true for R&D and brand.

It is unlikely that measurement error is responsible for our results. If anything, measurement error in the IT hardware, R&D, or brand variables would strengthen our conclusions, as measurement error in these variables would bias the coefficients downwards (Griliches and Hausman, 1986). Measurement error would also not explain why our ITC variable works in order in explaining differences in market value. We also reran all specifications without advertising and R&D altogether, and all the same results for IT hold. We further examine whether our results hold if we drop values from 2003 and 2004. The 2003 and 2004 IT asset stocks rely more on imputation than the 2005 and 2006 values of IT (because our IT spending data runs from 2003-2006). As well, since our organizational IT and management practice data was measured in 2005 and 2006, by dropping 2003 and 2004 we can examine whether our assumption that ITC is quasi-fixed and thus applicable to 2003 and 2004 is acceptable. Our main results still hold based only on 2005 and 2006 values for each firm.

CONCLUSION

Using a panel of 130 firms over the period 2003-2006, our study is the first to create comprehensive asset stocks based on IT-related intangible spending at the firm level. We build upon the framework by Brynjolfsson, Hitt and Yang (2002) who found that $1 of computer hardware was correlated more than $10 of market value, and that this value was accounted for by a set of complementary human resource practices. With our expanded definition of IT, that includes both purchased and internally developed software, internal IT services, external IT services, and IT-related training, we estimate these values – the "other $9" – directly in a market value equation.

Our results suggest that IT is not a "rising tide that lifts all boats." By using survey data that takes account of management and organizational IT capabilities (e.g., HR practices, management practices, internal IT use, external IT use, and Internet use), we find that these capabilities can help account for the value of IT intangibles. Firms with the highest IT capabilities (ITC) are correlated with significantly higher market value that the firms with the lowest IT capabilities. Holding fixed all tangible and intangible assets of the firm, we estimate that the firms in the highest ITC group have 30-55% greater market value than the firms in the lowest ITC group. We actually estimate that for every $1 of our broadest measure of IT, firms in the lowest ITC group realize a *loss* of $9 of market value.

Our study also uses market valuation techniques to value research and development (R&D) and brand as part of a broader effort to examine the value of intangible assets in the firm. Based on our results that R&D and brand are correlated with significantly higher market value, further research is warranted on which industries and firms drive most of this value. The results suggest that what will differentiate firms in the 21st century will be how they manage their intangible assets.

APPENDIX A. TABLES AND FIGURES

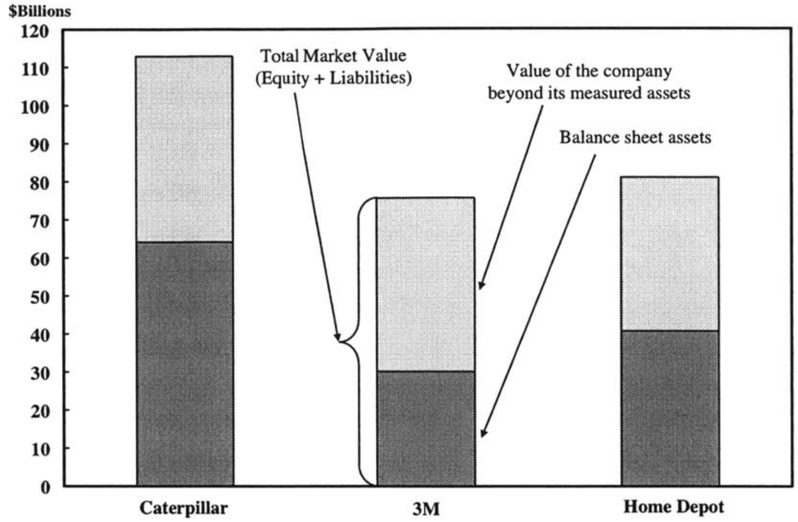

Figure 1. The Value of Three Components of the Dow Jones Industrial Average as Compared to their Balance Sheet Assets. Data from December 31, 2010.

Table 1. Variable Means for Sample, 2003-2006 ($Millions)

	Mean	Std. Deviation	Minimum	Maximum*
1. Market Value	31,095.0	59,672.7	295.7	353,935.7
2. IT Capital – purchased hardware	45.0	88.4	0.2	493.0
3. IT Capital – capitalized hardware and software	202.9	354.6	1.4	1,869.0
4. IT Capital – all capitalized and uncapitalized hardware, software, plus services, training, and leases converted to asset stocks.	562.9	1,080.8	4.6	6,285.3
5. Ordinary Capital (when IT defined as line 3 or line 4)	9,511.2	18,769.3	3.9	110,629.6
6. Other Assets	11,617.9	35,193.2	26.4	229,411.8
7. R&D Capital	2,529.2	7,495.2	0	44,004.9
8. Brand Capital	337.1	946.4	0	5,891.8

*To avoid disclosure, we list the maximum as the average of the 10 largest observations.

Table 2. Average IT Spending per Firm, 2003-2006 ($Millions)

		Mean	Standard Deviation	Minimum	Maximum*
1.	Hardware	32.4	61.9	0.2	343.5
2.	Prepackaged Software	37.1	66.9	0.3	370.2
3.	External IT Services (e.g., custom software, business process consulting, integration services)	47.0	89.5	0.3	503.5
4.	Internal IT Services (e.g., own-account software, design, maintenance, administration)	129.2	236.6	0.9	1,337.5
5.	IT-related Training	12.8	23.6	0.03	131.1
	Total IT Spending	**258.5**	**469.3**	**1.9**	**2,627.7**

*To avoid disclosure, we list the maximum as the average of the 10 largest observations.

Table 3. Capitalization Ratios of Hardware and Software Spending for 2003-2006 Sample

	Spending Type	Mean	Standard Deviation	Minimum	Maximum
1.	Hardware purchases and leases	100.0%	---	---	---
2.	Purchases, capitalized	64.0%	10.0%	51.2%	84.7%
3.	Purchases, not capitalized	18.2%	6.2%	5.4%	30.0%
4.	Leases, not capitalized	17.8%	5.2%	5.4%	26.0%
5.	Software purchases, payroll, and licensing	100.0%	---	---	---
6.	Purchases and payroll, capitalized	53.1%	8.7%	26.5%	68.7%
7.	Purchases and payroll, not capitalized	24.9%	8.1%	12.0%	56.8%
8.	Leases, not capitalized	22.0%	3.9%	11.6%	34.9%

Table 4. Average IT Stocks by Firm for 2003-2006 Sample ($millions)

	Asset	Capitalized	Not Capitalized	Total	Avg. Depreciation Rate	Average Annual Price Change for new Investment
1.	Hardware	34.2	21.5	**55.7**	30.8%	-13.2%
2.	Prepackaged Software	28.8	27.2	**56.0**	40.6%	-4.3%
3.	Custom Software	28.6	16.5	**45.1**	28.2%	1.2%
4.	Own-Account Software	111.3	63.1	**174.4**	27.2%	1.2%
5.	External IT Services (other than software design, e.g., business process consulting, integration services)	0	69.0	**69.0**	37.2%	1.0%
6.	Internal IT Services (other than software design, e.g. maintenance and administration)	0	135.0	**135.0**	37.2%	1.0%
7.	Training	0	27.8	**27.8**	37.2%	1.0%
	Total	**202.9**	**360.0**	**562.9**		

Table 5. Components of IT Capabilities (ITC)

ITC is the standardized sum (mean 0, standard deviation 1) of the five factors below.

Please rate whether the following factors at your company facilitate or inhibit the ability to make new information technology investments on a scale from 1 to 5, with 1 being "inhibits significantly," 3 being "no effect," and 5 being "facilitates significantly."		
HR Capabilities	**Average**	**Std. Dev.**
Technical skills of existing IT staff	4.57	0.50
Business skills of existing IT staff	4.53	0.50
Ability to hire competent IT staff	2.53	1.18
Skills of end-users	3.55	0.57
Management Capability		
Business Unit involvement in IT projects	2.60	1.14
Senior Management Support	2.56	1.16
Please rate how important the following methods are for *(internal communications, communications with suppliers)* in your company on a scale from 1 to 5, with 1 being "not at all important," 3 being "moderately important," and 5 being "extremely important."		
Internal IT Use		
Email	4.53	0.50
Mobile Electronic Mail (e.g., BlackBerry)	4.48	0.50
Instant Messaging	3.63	0.59
Company Intranet	3.55	0.55
Wireless (including phone and pager)	4.44	0.50
Supplier IT Use		
Email	4.54	0.50
Mobile Electronic Mail (e.g., BlackBerry)	4.56	0.50
Instant Messaging	3.50	0.50
Internet	3.60	0.49
Wireless (including phone and pager)	4.44	0.50
Please identify to what extent your company uses Internet technology to perform each of the tasks on a scale from 1 (no use of the Internet) to 5 (fully automated via the Internet).		
Internet Capability		
Sales force management	4.54	0.50
Employee performance measurement	3.10	0.89
Training	3.11	0.84
Post-sales customer support	3.00	0.86

Table 6. Distribution of Capabilities (ITC)

Category	Meaning	Number of Observations
ITC_A	ITC > 1.5	20
ITC_B	0.5 < ITC <= 1.5	152
ITC_C	-0.5 < ITC <=0.5	196
ITC_D	-1.5 < ITC <= -0.5	108
ITC_F	ITC < -1.5	44
Total		**520**

Table 7. Sector Dummy Variables

Sector Dummy Variables	NAICS Codes	Observations
1. Agriculture, Mining, Utilities Construction	11, 22, 21, 23	36
2. Nondurable Process Manufacturing:	322, 324, 325	104
Paper products; Petroleum and Coal products; Chemical products		
3. Other Nondurable Manufacturing:	311-316, 323, 326	28
Food, Beverage and Tobacco products; Textile Mills and Textile Product Mills; Apparel and Leather and Allied products; Printing and related support activities; Plastics and Rubber products		
4. Durable Manufacturing, High-Tech:	334, 335, 336	44
Computer and electronic products, Electrical equipment, appliances and components; Motor Vehicles, bodies and trailers, and parts; and Other transportation equipment		
5. Durable Manufacturing, non High-Tech:	321, 327, 331, 332, 333, 337, 339	80
Wood products; Nonmetallic Mineral products; Primary Metals; Fabricated Metal products; Machinery; Furniture and related products; Miscellaneous manufacturing		
6. Wholesale and Retail Trade	44-45	68
7. Transportation and Warehousing	48-49	36
8. Information	51	32
9. Finance and Insurance (*companies excluded, no observations*)	52	0
10. Real Estate and Rental and Leasing, Professional, Scientific and Legal Services; Management of Companies and Enterprises; Administrative and Support services, Waste Management and Remediation Services	53, 54, 55, 56	32
11. Educational Services; Health Care and Social Assistance	61, 62	24
12. Arts, Entertainment and Recreation; Accommodation and Food Services; Other Services except Government	71, 72, 81	36
	Total	**520**

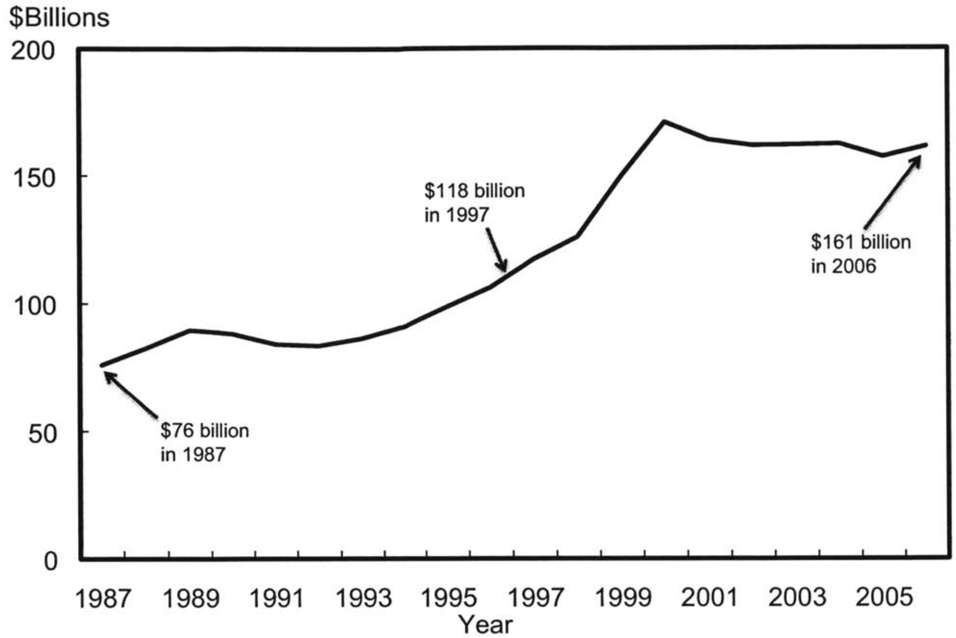

Figure 2. Computer Hardware Owned by Businesses in the United States, 1987-2006. Source, BEA Fixed Assets Table 2.1, "Current-Cost Net Stock of Private Fixed Assets, Equipment and Software, and Structures by Type," Line 5.

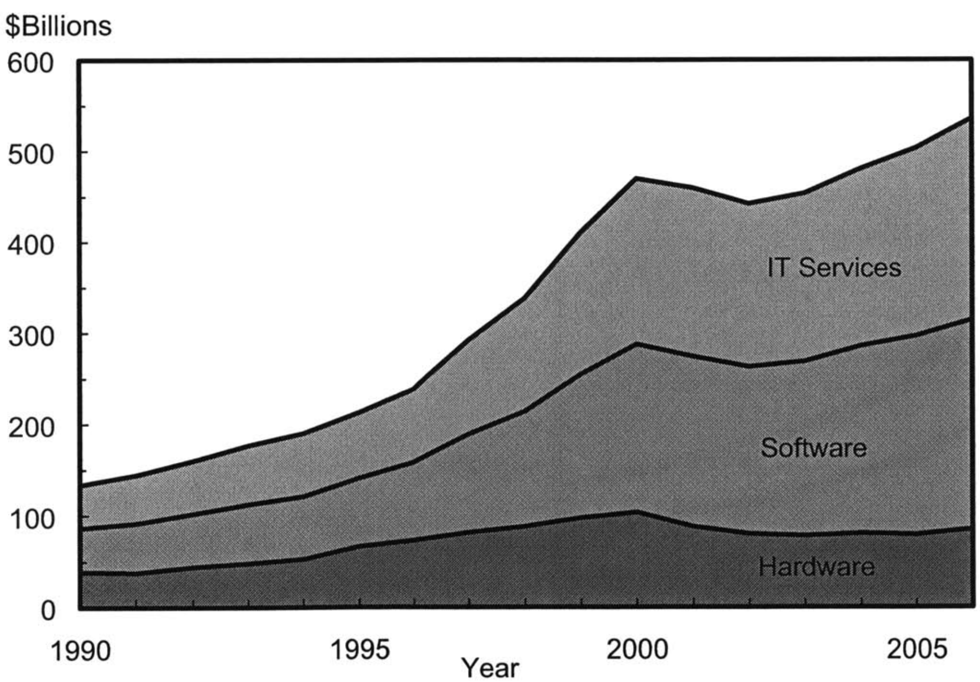

Figure 3. IT Spending by Businesses in the United States, 1990-2006. Sources: BEA NIPA Table 5.3.5, "Private Fixed Investment by Type," and authors' calculations from the Census Bureau's *Service Annual Survey*.

Table 8. Financial Value as a Function of the Assets of the Firm, 2003-2006

	(1)	(2)	(3)	(4)	(5)	(6)
Information Technology (*IT*) = Hardware	11.46	10.97				
	(3.08)	(3.28)				
Information Technology (*IT*) = Hardware, Capitalized Software			4.59	3.41		
			(1.05)	(0.94)		
Information Technology (*IT*) = Hardware, Capitalized Software, Other Intangibles					1.16	0.89
					(0.33)	(0.29)
Ordinary Capital (*K*)	1.02	0.87	1.01	0.86	1.03	0.87
	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)	(0.05)
Other Assets (*F*)	1.14	1.03	1.15	1.04	1.14	1.03
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
R&D (*R*)		1.43		1.46		1.44
		(0.27)		(0.26)		(0.27)
Brand (*B*)		7.87		8.01		7.92
		(1.58)		(1.55)		(1.58)
Number of Observations	520	520	520	520	520	520

Note: All regressions are GLS, with correction for heteroskedasticity and serial correlation. Sector and year dummies are included, as well as dummies for no R&D and whether advertising was imputed.

Table 9. Financial Value as a Function of the Assets of the Firm and ITC, 2003-2006

	(1)	(2)	(3)	(4)
Information Technology (*IT*) = Hardware, Capitalized Software	2.84	-0.61		
	(0.94)	(2.02)		
Information Technology (*IT*) = Hardware, Capitalized Software, Other Intangibles			0.74	0.01
			(0.27)	(0.70)
Ordinary Capital (*K*)	0.94	0.89	0.93	0.90
	(0.07)	(0.06)	(0.06)	(0.06)
Other Assets (*F*)	0.99	1.01	1.00	1.02
	(0.06)	(0.06)	(0.06)	(0.06)
R&D (*R*)	1.77	1.44	1.79	1.47
	(0.29)	(0.27)	(0.28)	(0.27)
Brand (*B*)	5.97	6.97	6.14	6.68
	(1.64)	(1.64)	(1.61)	(1.63)
ITC > 1.5	3,951	-2,832	3,999	-2,570
(ITC_A = 1)	(2,304)	(1,731)	(2,257)	(1,752)
0.5 < ITC < 1.5	2,372	-1,063	2,651	-652
(ITC_B = 1)	(790)	(919)	(761)	(922)
-1.5 < ITC < -0.5	-1,281	-2,451	-1,273	-2,129
(ITC_D = 1)	(901)	(959)	(868)	(952)
ITC < -1.5	-5,066	-8,488	-4,925	-8,300
(ITC_F = 1)	(2,022)	(2,304)	(1,976)	(2,333)
IT*ITC_A		71.02		25.81
		(18.45)		(6.90)
IT*ITC_B		15.97		5.50
		(3.69)		(1.36)
IT*ITC_D		3.43		0.76
		(2.29)		(0.76)
IT*ITC_F		14.94		5.55
		(8.08)		(3.24)
Number of Observations	520	520	520	520

Note: All regressions are GLS, with correction for heteroskedasticity and serial correlation. Sector and year dummies are included, as well as dummies for no R&D and whether advertising was imputed.

APPENDIX B. CALCULATION OF ORDINARY CAPITAL

We define physical capital as the sum of equipment, structures, land, and inventories, according to the BLS definition of capital. Ordinary, or Non-IT capital, is thus sum of four types of capital: Non-IT equipment, structures, land, and inventories.

Inventories

We take the value directly from the *Compustat* (mnemonic INVT). We do not transform this variable, and assume it is a reasonable estimate for the current-cost wealth stock.

Structures and Land

We begin with PPENT, *Compustat's* mnemonic for the net book value of property, plant, and equipment. This consists of equipment, structures, and land. However, there is no further classification of the capital stock by type because publicly traded companies are not required to disaggregate their capital stock in their filings. Thus, we disaggregate the firm's capital stock assuming the industry mix of equipment, structures, and land. There are two complications, however. The first is that the BEA, which publishes historical cost stocks and current dollar stocks of capital at the industry level, does not include land in its estimates. The second is that the BLS, which publishes current-cost industry-level capital stocks that include land, does not publish historical-cost estimates. Thus, we combine both data sources to compute a historical to current cost ratio of equipment, structures, and land by industry, which can then be applied against the firm-level net historical-cost stocks of capital.

We begin by converting the BLS industry data from constant dollar productive stocks to current-dollar productive stocks using BLS Tables 4a and 8b. We then use BEA Fixed Assets Tables 3.3E and 3.3S respectively to convert equipment and structures from current-cost to historical-cost dollars. We then impute the historical-cost value of land by using the BLS current-cost estimate of land times the BEA ratio of historical to current cost for structures for that industry. (We assume that the ratio of historical-cost estimate to current-cost estimate of land is the same as that for structures.)

We use our historical-cost estimates for each industry to match against *Compustat's* PPENT field, a firm-level historical-cost net stock of equipment, structures, and land. We estimate firm-level equipment by multiplying PPENT by the industry average ratio of equipment to the total of equipment, structures, and land. We illustrate in equation (B.1):

$$E_{firm}^{hist} = PPENT \cdot \frac{E_{indu}^{hist}}{E_{indu}^{hist} + S_{indu}^{hist} + L_{indu}^{hist}} \qquad \text{(B.1)}$$

Where E_{firm}^{hist} is net equipment at the firm level in historical-cost dollars. E_{indu}^{hist} is aggregate equipment at the industry level, in historical cost dollars, from BEA Table 3.3E. S_{indu}^{hist} is the historical-cost stock of structures for the industry, from BEA Table 3.3S. L_{indu}^{hist} is the historical cost of land, which we imputed as described above.

To convert E_{firm}^{hist} to a current-dollar estimate, we multiply it by the industry ratio of equipment in current cost dollars to historical cost dollars.

$$E_{firm}^{cur} = E_{firm}^{hist} \cdot \frac{E_{indu}^{cur}}{E_{indu}^{hist}} \qquad \text{(B.2)}$$

Where E_{indu}^{cur} is the aggregate of equipment by industry in current costs, from BEA Fixed Assets Table 3.1E. We do the same thing for structures. For land, since the BEA does not publish historical or current cost estimates of land by industry in the Fixed Assets tables, we use the same historical to current ratio as structures:

$$L_{firm}^{cur} = L_{firm}^{hist} \cdot \frac{S_{indu}^{cur}}{S_{indu}^{hist}} \qquad \text{(B.3)}$$

For two industry pairs, we make slight adjustments because the BLS aggregates BEA codes 336M and 336O together into one industry code, and also aggregates BEA codes 622H and 6230 into one industry code. The BEA publishes current-cost and historical-cost industry data for each of these BEA-codes separately. Therefore, we allocated land for the 336M + 336O pair into each of their components 336M, and 336O, by the ratio of the BEA estimates of structures for the industry (336M) to the BLS estimate of structures for the pair (336M + 336O).[19]

Non-IT Equipment

We estimate current-cost non-IT equipment from estimate of equipment at the firm level minus our measure for IT (whether it is hardware only, or capitalized IT). We drop observations in which our estimate for non-IT equipment is 0, as our IT estimate has a potentially serious measurement issue, or the firm uses a very different mix of equipment, structures and land from the rest of the industry. This affects only a small handful of firms in our sample, however.

[19] Both the BEA and BLS have publicly available industry-level estimates of equipment and structures for each industry. Because they make different assumptions about deprecation, the estimates are close, but not the same (usually they are within 10% of each other).

REFERENCES

Aizcorbe, A. M., Moylan, C. E., and Robbins, C. A. 2009. "Toward Better Measurement of Innovation and Intangibles," *Survey of Current Business* (89:1), January, pp. 10-23.

Anderson, M.C., Banker, R.D., and Ravindran, S. 2003. "The New Productivity Paradox," *Communications of the ACM* (46:3), March, pp. 91-94.

Aral, S., and Weill, P. 2007. "IT Assets, Organizational Capabilities, and Firm Performance: How Resource Allocations and Organizational Differences Explain Performance Variation," *Organization Science* (18:5), September-October, pp. 763-780.

Baily, M.N. 1981. "Productivity and the Services of Capital and Labor," *Brookings Papers on Economic Activity* (1981:1), pp. 1-65.

Bartel, A., Ichniowski, C., and Shaw, K. 2007. "How does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills," *Quarterly Journal of Economics* (122:4), November, pp. 1721-1758.

Barth, M.E., Clement, M.B., Foster, G., and Kaznik, R. 1998. "Brand Values and Capital Market Valuation," *Review of Accounting Studies* (3:1-2), March, pp. 41-68.

Bloom, N., Sadun, R., and Van Reenen, J. 2007. "Americans Do I.T. Better: US Multinationals and the Productivity Miracle," *NBER Working Paper* 13085, May.

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

Brynjolfsson, E., Fitoussi, D., and Hitt, L. M. 2005. "The Information Technology Iceberg," MIT Center for Digital Business Working Paper, May.

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

Brynjolfsson, E., Hitt, L. M., and Yang, S. 2002. "Intangible Assets: Computers and Organizational Capital," *Brookings Papers on Economic Activity* (2002:1), pp. 137-181.

Brynjolfsson, E., McAfee, A., Sorell, A., and Zhu, F. 2009. "Scale without Mass: Business Process Replication and Industry Dynamics," Working paper, MIT.

Brynjolfsson, E., Renshaw, A.A., and Van Alstyne, M. 1997. "The Matrix of Change," *Sloan Management Review* (38:2), Winter, pp. 37-54.

Bureau of Economic Analysis. 2000. Recognition of Business and Government Expenditures for Software as Investment: Methodology and Quantitative Impacts, 1959-98," Washington, DC. May.

Bureau of Economic Analysis. 2003. *Fixed Assets and Consumer Durable Goods in the United States, 1925-97*, Washington, DC: U.S. Government Printing Office.

Bureau of Labor Statistics. 1983. *Trends in Multifactor Productivity, 1948-81,* BLS Bulletin 2178.

Cheng, Z.J., and Nault, B.R. 2007. "Industry Level Supplier-Driven IT Spillovers," *Management Science* (53:8), pp. 1199-1216.

Corrado, C., Hulten, C., and Sichel, D. 2005. "Measuring Capital and Technology: An Expanded Framework," in *Measuring Capital in the New Economy*, C. Corrado, J. Haltiwanger, and D. Sichel (eds.), Chicago: University of Chicago Press, pp. 11-46.

Corrado, C., Hulten, C., and Sichel, D. 2009. "Intangible Capital and Economic Growth," *Review of Income and Wealth* (55:3), September, pp. 661-685.

Crespi, G., Criscuolo, C., and Haskel, J. 2007. "Information Technology, Organisational Change, and Productivity Growth: Evidence from UK Firms," *CEP Discussion Paper No. 783*, March.

David, P.A. 1990. "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox," *The American Economic Review* (80:2), May, pp. 355-361.

Dedrick, J., Gurbaxani, V., and Kraemer, K. L. 2003. "Information Technology and Economic Performance: A Critical Review of the Empirical Evidence," *ACM Computing Surveys* (35:1), March, pp. 1-28.

Dewan, S., Shi, C., and Gurbaxani, V. 2007. "Investigating the Risk–Return Relationship of Information Technology Investment: Firm-Level Empirical Analysis," *Management Science* (53:12), December, pp. 1829-1842.

Griliches, Z., and Hausman, J.A. 1986. "Errors in Variables in Panel Data," *Journal of Econometrics* (31:1), February, pp. 93-118.

Gu, F., and Lev, B. 2002. "Intangible Assets: Measurement, Drivers, Usefulness," Working Paper, Stern School of Business, New York University.

Hall, B.H., Jaffe, A., and Trajtenberg, M. 2005. "Market Value and Patent Citations," *The Rand Journal of Economics* (36:1), Spring, pp. 16-38.

Hall, R. E. 2000. "E-Capital: The Link between the Stock Market and the Labor Market in the 1990s," *Brookings Papers on Economic Activity* (2000:2), pp. 73-118.

Hall, R. E. 2001. "The Stock Market and Capital Accumulation," *The American Economic Review* (91:5), December, pp. 1185-1202.

Hand, J.R.M. 2003. "The Increasing Returns-to-Scale of Intangibles," in *Intangible Assets: Values, Measures and Risks*, J. Hand and B. Lev (eds.), New York: Oxford University Press, pp. 303-331.

Kaplan, R.S., and Sandino, T. 2001. "Accounting for Computer Software Development Costs," Harvard Business School Note 102-034.

Lev, B. 2004. "Sharpening the Intangibles Edge," *Harvard Business Review* (82:6), June, pp. 109-116.

Lev, B., and Radhakrishnan, S. 2005. "Valuation of Organizational Capital," in *Measuring Capital in the New Economy*, C. Corrado, J. Haltiwanger, and D. Sichel (eds.), Chicago: University of Chicago Press, pp. 73-110.

McKinsey Global Institute. 2001. U.S. Productivity Growth 1995-2000: Understanding the Contribution of IT Relative to Other Factors. Available at http://www.mckinsey.com.

Mead, C.I. 2007. "R&D Depreciation Rates in the 2007 R&D Satellite Account," Bureau of Economic Analysis/National Science Foundation 2007 R&D Satellite Background Paper, November.

Milgrom, P., and Roberts, J. 1990. "The Economics of Modern Manufacturing: Technology, Strategy, and Organization," *The American Economic Review* (80:3), June, pp. 511-528.

Milgrom P., and Roberts, J. 1995. "Complementarities and Fit: Strategy, Structure and Organizational Change in Manufacturing," *Journal of Accounting and Economics* (19:2-3), March-May, pp. 179-208.

Nakamura, L. 2001. "What is the U.S. Gross Investment in Intangibles? (At least) One Trillion Dollars a Year!" *Working Paper No. 01-15, Federal Reserve Bank of Philadelphia.* October.

Oliner, S.D., Sichel, D.E., and Stiroh, K.J. 2007. "Explaining a Productive Decade," *Brookings Papers on Economic Activity* (2007:1), pp. 81-152.

Pilat, D. 2004. "The ICT Productivity Paradox: Insights from Micro Data," *OECD Economic Studies* (38:1), pp. 37-65.

Porter, M.E. 1996. "What is Strategy?" *Harvard Business Review* (74:6), November-December, pp. 61-78.

Seethamraju, C. 2003. "The Value Relevance of Trademarks," in *Intangible Assets: Values, Measures and Risks*, J. Hand and B. Lev (eds.), New York: Oxford University Press, pp. 228-247.

Tambe, P. and Hitt, L.M. 2010. "Job Hopping, Knowledge Spillovers, and Regional Returns to Information Technology Investments." SSRN Working Paper, March. Available at SSRN: http://ssrn.com/abstract=1302637

Zhao, R. 2002. "Relative Value Relevance of R&D Reporting: An International Comparison," *Journal of International Financial Management and Accounting* (13:2), Summer, pp. 153-174.

Chapter 2

Has Information Technology Leveled the Competitive Playing Field?

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This paper analyzes the relationship between IT and ordinary (non-IT) capital and the competitive dynamics within U.S. industries. Using a panel of industry data from 1998-2005, I investigate whether IT has leveled the competitive playing field between small and large firms. I address three questions: (1) Is IT affecting barriers to entry? (2) What is the relationship between IT capital and the rate of turnover among small firms in an industry? (3) Is more IT associated with industries becoming more concentrated in smaller or larger firms? As to whether IT levels the competitive playing field, my results are mixed. When an industry becomes more IT intensive, there is more entry and expansion of firms (including entry of new small firms and expansion of large firms from the same and other industries). Yet there is also more turnover of small firms in the industry as well as concentration of the industry into large firms. In contrast, as an industry becomes more ordinary capital-intensive, there is less entry of small firms and fewer establishment openings by large firms; a lower rate of turnover by small firms; and fragmentation of the industry into small firms. My results further suggest that in IT intensive environments, large firms use business process replication to expand their share of the market, and in less IT intensive environments, small firms may be operating in more niche markets, thus avoiding direct competition with larger firms. This paper contributes to existing literature on IT and the boundaries of the firm.

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Introduction

Information technology (IT) enables small businesses to easily connect with suppliers and customers across the United States and around the world. Moreover, high-tech startups that originate in garages, basements, or college dorm rooms use IT to compete with the mightiest of companies in ways that would have been impossible 50 years ago. Anyone with a web connection has the potential to reach millions. Yet has IT really leveled the competitive playing field between small and large firms in the U.S. economy?

In this paper, I investigate the following questions: (1) Does more capital per firm in an industry serve as a barrier to entry, as previous theory would indicate, or is IT a unique kind of capital that affects barriers to entry? (2) Has IT increased the rate of turnover among small firms in the industry? (3) Is IT associated with fragmentation of the industry into small firms, or concentration into large firms?

In order to answer these questions, I begin by analyzing the relationship between IT and ordinary (non-IT) capital per employee in an industry and the total number of small entrants and large firm expansions in that industry. I examine whether, as an industry becomes more IT-intensive, more establishment openings are by small firms (with less 20 employees) or by large firms (with 500 or more employees). I then investigate the relationship between capital and both firm turnover and industry concentration. I conduct this study based on industry-level data from the U.S. Census Bureau, the Small Business Administration, and the Bureau of Economic Analysis. My results are based on fixed effects specifications on a panel of 53 industries in the United States during the period from 1998 to 2005.[1]

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[1] These are industries that do not produce IT. Further details of industry classification are provided in Section 3 (Data) and Appendix B.

As to whether IT levels the competitive playing field between small and large firms, my results suggest a mixed picture. When an industry becomes more IT intensive, I find that there is more entry and expansion of firms (including entry of new small firms and expansion of large firms from the same and other industries), but there is also more turnover of small firms in the industry as well as concentration of the industry into large firms. I further elaborate on these points below.

My results indicate that IT capital affects barriers to entry for small and large firms. As an industry becomes more IT capital-intensive, there are more small entrants as well as more establishment openings by large firms. This dynamic stands in contrast to my finding that as an industry becomes more capital intensive (as defined by IT plus ordinary capital per firm), there are fewer small entrants and less establishment openings by large firms. Likewise, increases in ordinary capital in an industry are also associated with reduced small firm entry and less expansion by large firms.

Comparing the source of establishment openings in an industry, I find that more IT capital per firm is strongly associated with greater large firm expansion relative to small firm entry. Establishment openings by large firms come from (1) firms already in the industry that add another establishment; and (2) firms in other industries that open an establishment in a different industry for the first time.

How does the entrance and expansion of large firms in IT-intensive industries affect the small firms? I find that as an industry becomes more IT intensive, there is more turnover among small firms.[2] In contrast, as an industry becomes more ordinary capital-intensive, there is less

[2] My measure of turnover is establishment births plus deaths throughout the year divided by the number of establishments at the beginning of the year.

turnover among small firms. For large firms, increases in capital intensity – whether it be IT or ordinary capital – does not change establishment turnover to a significant extent.

Lastly, I find that as an industry becomes more IT intensive, small firms make up a smaller percentage of the industry's total firms. In other words, there is more concentration of the industry into large firms. This means that small firms are entering more IT intensive industries despite the fact that there is greater turnover among small firms and that large firms expand to take up a greater share of the industry. That is, small firms are entering industries that become more IT intensive even though conditions do not appear to favor small firm survival. In contrast, although an increase in ordinary capital in an industry is associated with less firm entry, it is also strongly associated with industry fragmentation into small firms.

Examining the relationship between IT capital and the competitive dynamics within industries has important implications for entrepreneurs and policymakers. For entrepreneurs, the relationship between IT, entry, and turnover can help guide investment decisions about whether to enter low-tech or high-tech industries. For policymakers, this study provides insights as to whether tax breaks or other incentives should be directed towards small or large firms, depending on whether the industry is becoming more technology-intensive or ordinary capital-intensive.

My paper contributes to literature on IT and firm boundaries. Much of the existing scholarship has focused on the role of IT in the context of large firms. There are a number of scholars that have studied the ways in which firms have transformed their businesses through technology-enabled organizational change.[3] Yet the literature that examines IT and small

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[3] See Brynjolfsson, Renshaw and Van Alstyne (1997) for a case study of IT-led process change in a large manufacturing company. Brynjolfsson, Hitt and Yang (2002) use a dataset of large firms to measure the value of IT in combination with high-performance workplace practices, and Bresnahan, Brynjolfsson and Hitt (2002) demonstrate that IT and workplace practices are associated with higher productivity. Further examples and case

business competitiveness is much less developed. In a literature review covering the 1986-1999 period, Burgess (2002, p.2) notes that the number of peer-reviewed articles that relate to IT and small firms constitute between just two-thirds of one percent to one percent of all peer reviewed articles about IT. Applying his methodology, I find little change in more recent years, with about one percent of scholarly articles from 2000-2007 relating to IT also relating to small firms. I argue that this understudied area is worthy of further research given that most firms in the economy are small—according to the U.S. Census Bureau, there were almost six million firms in the United States in 2005, and nine out of every ten of them employed less than 20 people.[4]

Analyzing the dynamics of small firms within IT-intensive industries has implications for the theory of the firm and, more specifically, how information technology is associated with changes to the boundaries of the firm. Coase (1937) was the first to consider the boundaries of the firm by exploring why transactions would be done inside a firm or by the market. Since Coase published his seminal work, there have been other scholars who have further explored firm boundaries.[5] Some topics they have been covered include transaction costs (Williamson 1981), property rights (Grossman and Hart 1986; Hart and Moore 1990), information uncertainty (Arrow 1974), and contingencies (Thompson 1967). Scholars have demonstrated that firms can provide the right incentives for employees to invest in specific skills or information. My paper contributes to this literature by examining whether IT is a unique kind of capital that allows

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studies can be found in Autor, Levy and Murnane (2002) and Bartel, Ichniowski and Shaw (2007). For a recent review of the literature in this area, see Saunders and Brynjolfsson (2007).

[4] U.S. Census Bureau, Statistics of U.S. Businesses 2005. Available at http://www.census.gov/epcd/susb/2005/us/US--.HTM

[5] A full examination of theories of the firm is well beyond the scope of this paper. The interested reader is advised to consult Gibbons (2005).

firms to enter industries and better coordinate activities among their establishments. It also considers whether information technology is associated with industry fragmentation into small firms, in which case markets would coordinate what was once done inside firms.

My paper addresses the large literature about the dynamics of competition among firms (Dierickx and Cool 1989; Hannan and Freeman 1977, 1984; Kogut and Zander 1992; Nelson and Winter 1982; Porter 1980; Schumpeter 1942; Teece, Pisano and Shuen 1997; Winter and Szulanski 2001; Zander and Kogut 1995). I contribute to the debate between IT, competition, and firm size. Leavitt and Whisler's 1958 *Harvard Business Review* article, one of the first to coin the term "information technology," predicted that IT would make the firm larger. Wilson (1975) argued that better information would lead to a larger scale of operations, which would then encourage the firm to acquire even better information, and so forth. In this model, the costs of gathering information declines with scale, whereas the value of information does not (p.189). Taken to the extreme, this virtuous cycle could continue without bound.[6]

On the other hand, the seminal work by Malone, Yates and Benjamin (1987, p.496) predicted "information technology will lead to an overall shift toward proportionately more use of markets rather than hierarchies to coordinate economic activity." This is because IT lowers coordination costs, such as scheduling, tracking financial flows, or negotiating contracts. This would mean that IT should be associated with smaller firms.

An empirical study by Brynjolfsson, Malone, Gurbaxani and Kambil (1994) confirmed this prediction and they conclude that IT is associated with smaller firms, based on data from 1976 through 1987. Another study by Brynjolfsson, McAfee, Sorell and Zhu (2007) examines the dynamics of competition in the U.S. economy with respect to more IT intensive versus less

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[6] Unbounded growth occurs assuming constant returns to scale in the production function. Wilson (1975) notes that of course, there will be eventually decreasing returns to scale which limits infinite growth.

IT intensive industries. It concludes that between 1987 and 2004, firms in IT intensive industries changed sales ranks more than the firms in less IT intensive industries. The change in sales rank measure is referred to as "industry turbulence." In a comparison between the pre-1996 and post-1996 periods, the authors determine that an industry's IT intensity was significant in explaining the increases in industry turbulence and the concentration in sales and enterprise value between the two time periods (p.19). My study contributes to this literature by examining establishment turnover of small and large firms in relationship to IT intensity. This measure is complementary to turbulence—industry turnover is one indication of the "creative destruction" (Schumpeter 1942) at work in an industry and complements my analysis of entry by focusing on existing firms.[7] By showing that small firms are subject to greater turnover as an industry becomes more IT-intensive, my study extends the findings by Brynjolfsson, McAfee, Sorell and Zhu (2007) that larger firms are subject to greater turbulence in IT-intensive industries.

What is missing from existing studies and what my paper provides is an examination of the relationship between IT and the dynamics of entry by both small and large firms based on recent industry-level data. My paper contributes to existing literature both in terms of its quality of data and the questions that it addresses. I use fixed effects estimation to examine changes within multiple industries from 1998-2005. My work examines the IT and firm size question first posed empirically by Brynjolfsson, Malone, Gurbaxani and Kambil (1994) but relies on more recent data that is more fine-grained, based on more industries and several size categories. It also supplements the work of Brynjolfsson, McAfee, Sorell and Zhu (2007) by going beyond the large firms in Compustat that they rely on and also examining small firms.

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[7] Since I use industry-level data, I do not have access to the sales ranks of individual firms and thus cannot measure industry turbulence.

Using this extensive data about establishment dynamics and firm size, my paper is the first to examine the association between IT and small firm entry into industries. My results contrast with Brynjolfsson, Malone, Gurbaxani and Kambil (1994) as I find that increased IT per firm is associated with fewer small firms and more large firms. By using Census data that is not restricted to a single industry for a given firm, I can ask previously unexamined questions such as whether large firms are branching out into new industries. As a result, I am able to analyze whether entry into IT-intensive industries is by new small firms, or large firms that are opening new establishments, or both.

THEORETICAL CONSIDERATIONS

To determine how capital intensity affects the dynamics of firms in an industry, consider the typical firm's cost function as the sum of fixed costs and variable costs:

$$C = F + c(x) \tag{1}$$

Where C is the firm's total costs, F is the firm's fixed costs, and $c(x)$ is the cost of output as a function of x, thereby making $c'(x)$ equal to the marginal costs of production. Let $c(x) = rK + wL$, where rK represents the cost of capital as rental price r times the stock of capital K. Let wL represent the cost of labor as the wage rate w times the number of employees L.

Barriers to Entry

My paper explores whether capital (including ordinary and IT capital) serves as a barrier to entry. In a dynamic economy, K should behave as more of a fixed cost than L. So as K increases with respect to L, then it is reasonable to expect that F would increase relative to $c(x)$.

There are several reasons why capital intensity may serve as a barrier to entry, especially for small firms.[8] Below I list five reasons cited by Tirole (1988, p.314-15 citing Bain 1956), including one that uses the Stackelberg-Spence-Dixit model of capital as a commitment device.

1) *Financing.* All else being equal, if an industry's production process tends to be very capital intensive, then small firms would likely find entry difficult because they need to raise more money to enter the market. It is going to be a lot easier to raise money to open a dry cleaning store than it is to start an oil refinery. Large incumbents will likely have a greater advantage in securing capital than relatively unproven entrants.

2) *Economies of Scale.* If $c''(x) < 0$, then there are economies of scale present in the production process. Naturally, this would favor large firm expansion.[9]

3) *Lower Marginal Costs.* As compared to new small firms, existing firms with large capital stocks may have lower marginal costs $c'(x)$, through learning by doing, research and development, or more favorable terms with suppliers. For example, the largest employer in the United States, Wal-Mart, uses its size as bargaining power to negotiate better terms with its suppliers, and thus offer lower prices than its competitors.

4) *Product-Differentiation Technologies.* Large firms may crowd the product space with niche products, thus making it difficult for small firms to enter an industry. For example, the Swedish Tobacco company, upon losing its government-protected monopoly status, doubled the number of brands it offered (Tirole 1998, p.346). Citing Schmalensee (1978), Tirole notes that "the six leading manufacturers of ready-to-eat breakfast cereals introduced eighty brands

[8] In 2004 (the year with the most recent data available), more than 4 out of every 5 establishment births in the United States represented new firms with less than 20 employees. The remainder of establishment births came mainly from expansions by firms with more than 500 employees. See Table 3 for details.

[9] In the case of a multi-product firm, economies of scope would favor expansion of the firm into other industries.

between 1950 and 1972 (the year in which the Federal Trade Commission issued a complaint against the four largest manufacturers), who had cornered 85 percent of the market and who enjoyed large profits."

5) *Commitment Device*. According to the Stackelberg-Spence-Dixit model, a large, illiquid capital stock could serve as a commitment device for an incumbent firm by signaling to potential entrants that entry would be unprofitable. The incumbent is, in effect, burning its bridges[10] and committing to remain in the market whether or not entry occurs, which might make potentially profitable entry unprofitable and deter entry altogether (*ibid,* p.314-315).

IT as a Unique Type of Capital

While capital may pose a barrier to entry for the reasons cited above, it is necessary to recognize that different types of capital will affect firm dynamics in different ways. IT is a unique kind of capital that allows for significantly greater coordinating activities within firms and better communication between firms (Brynjolfsson, Malone, Gurbaxani and Kambil, 1994). In this vein, I argue that it is important to consider IT and ordinary capital separately when considering F and $c(x)$.

IT capital can enable small firms to be on more favorable competitive terms with respect to larger firms. For example, with better communication and coordination, a firm could theoretically be located anywhere. Consider a firm that opens in New Jersey instead of New York City and, as a result, pays lower real estate costs. IT also allows for other costs to be outsourced, such as human resources or other administrative activities. By enabling better

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[10] Dixit and Nalebuff (1991, p.169) note that this strategy dates back to at least 1066 when William the Conqueror ordered his invading armies to burn their ships. This committed the armies to fight to win, as retreat was no longer an option.

communication between firms, small firms could significantly lower F and enter markets that otherwise would be too unprofitable to enter.[11]

However, it is important to realize that large firms also benefit from better internal coordination afforded by IT, potentially more so than small firms.[12] This would enable large firms to grow even larger and achieve greater economies of scale and scope. A firm can coordinate activities and create synergies that would not be possible without IT. For example, it can use IT to extend its particular business model to branch out and open establishments in several different industries. In this case, the large firm leverages IT to extend its business model, and the specific industry where it does so is of secondary concern.[13]

Thus, as an industry becomes more IT capital-intensive, there are multiple sources of entry: from smaller firms that reduce their fixed costs to compete with larger firms, or from large firms that utilize economies of scope to extend their business model into other industries.[14] My econometric model, described in Section 4, addresses this issue. I examine the rate of small entry and large expansion per 100 establishment openings in an industry, which allows for a direct comparison of the sources of establishment growth.[15]

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[11] Large firms also benefit from lower external communication costs, although I argue that lower communication costs will benefit small firms more.

[12] While small firms also benefit from better internal coordination, most small firms are single-establishment locations in which face-to-face communication with everyone else is possible.

[13] See Weill et al (2005) for their classification system of the economy into 16 basic business models as an alternative to the traditional industry classification system.

[14] In addition, a large firm already in the industry that opens more establishments in new locations could be considered entry into different geographic markets, for example.

[15] More than 94% of establishment openings in 2004 in the United States were either small firms opening their first establishment, or large firms opening a secondary establishment.

Data

Using publicly available data, I create a panel dataset at the industry level from 1998-2005. I begin with the 63 industries that the Bureau of Economic Analysis (BEA) uses to report industry-level data in the National Income and Product Accounts (NIPA).[16] I then condense these to 56 industries due to differences in industry aggregation between various government sources.[17] I further narrow the sample to 53 IT-using (or non-IT producing) industries by dropping Computer and Electronic Products (NAICS 334), Information (NAICS 51),[18] and Computer Design and Related Services (5415), for a total of 371 industry-year observations.[19] The remaining industries are at the 2 or 3 digit NAICS level.

For each measure below, I use the following data sources. Further information and the links to download this data are contained in Appendix B.

Firm and Establishment Births and Deaths

I use data from the Small Business Administration (SBA), Office of Advocacy, "Statistics of U.S. Businesses and Nonemployer Statistics." The SBA compiles this data from the Census Bureau's Statistics of U.S. Businesses, "Number of Firms, Number of Establishments, Employment, and Annual Payroll by Employment Size of the Enterprise for the United States, All Industries." The number of firms and establishments are reported on March 12th of each year. Establishments are classified in a unique industry according to the majority of

[16] This is based on the 1997 NAICS categories.

[17] I further describe this process in Appendix B.

[18] Ideally, I would drop just the IT-producing industries of Software Publishers (NAICS 5114) and Information and Data Processing Services (NAICS 514) instead of the entire Information sector (NAICS 51) (which includes those industries plus others). But in 2003, detailed Information industries (at the 3 digit NAICS level) were completely reclassified within the NAICS system, making it impossible to match the public data before and after the change. Therefore, I aggregated the industries to the 2-digit sector level (NAICS 51), which could be smoothly matched across all the years in the sample.

[19] As I detail below, because I match stock to flow data, I lose one year so that I have seven matched years worth of data.

that establishment's activities. Thus, each establishment appears only once in the industry-level data. However, a firm is counted as being in an industry if it has at least one establishment in that industry. Therefore, a multi-unit firm can appear in several industries, a fact that I exploit in my interpretation of the results.[20]

Capital Stocks

This data comes from the BEA Detailed Fixed Assets Tables. The two tables are called "Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets" and "Chain-Type Quantity Indexes for Net Capital Stock of Private Nonresidential Fixed Assets." For IT equipment, I combine three categories: 1) Computers and Peripherals, 2) Software, and 3) Communications Equipment. I then deflate IT and ordinary capital into constant 2000 dollars through a procedure that I describe in Appendix B.

Industry-Level Employment

Data on this measure comes from BEA NIPA Table 6.5D, "Full-Time Equivalent Employees by Industry." It is defined as the number of full-time employees in the industry, plus the number of part-time employees (that are converted to a full-time basis).

Data Matching

When assembling the dataset, I matched flow data to stock data in the following way. Industry-level employment is reported on a calendar-year basis. Capital stock data is reported as

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[20] For example, consider Microsoft, which employs approximately 55,000 people in the United States. Suppose that hypothetically, all of the employees work in the software publishing industry. Then suppose that the firm opens a stand-alone restaurant in downtown Seattle using 10 of its employees. According to the firm count data, the company would appear once in the software industry and once in the food services industry, each time as a firm with more than 500 employees that has operations in that industry (because the size of the *entire* firm is considered in the firm size classifications). In other words, in the restaurant industry, Microsoft's restaurant would appear as one establishment with 10 people, belonging to a firm with 500 or more employees. I should note that in this hypothetical example, it matters where the restaurant is located and whether it is considered to be a separate establishment. If it were part of an establishment on the Microsoft campus, then it would not appear in the restaurant industry; rather, it would be counted in the software industry.

of December 31st, and firm and establishment counts are from March 12th. Therefore, I match March 12, 2005 firm count data to the 2004 industry employment data, and then to the December 31, 2004 capital stock data. Other years follow the same pattern. The first year in my sample is 1998, which is matched to March 12, 1999 firm counts. Therefore, there are 7 years worth of matched data.

My dataset has the following limitations. One is that my first industry-year observations begin in 1998, and in terms of information and communications technologies, 1995 marked a watershed year of Internet adoption. I am constrained from using earlier years due to the switchover from SIC to NAICS industry codes by the U.S. government. My matches from 1998-2005 are all consistent with each other because the data is in NAICS. By attempting to combine SIC and NAICS, I risk affecting my entry and expansion results, which could be sensitive to changing industry definitions.

I cannot directly observe firm or industry costs, and so I assume that capital is a fixed cost. I also cannot observe capital stocks beyond the 2 or 3 digit NAICS level, and thus, all data in my analysis is summed to this level of aggregation.[21]

Descriptive Statistics

Table 1 lists the summary statistics for the 53 IT-using industries from 1998-2004.[22] For a perspective on the U.S. economy as a whole, Table 2 lists value-added per employee, ordinary capital per employee, and IT capital per employee for each year from 1998-2004. There is a significant difference between the growth rates of IT and ordinary capital per worker in the U.S.

[21] Firm-level IT data is very difficult to obtain, especially for small companies. The U.S. Census Bureau has firm-level data for IT investment at the firm level, but this series begins only in 2003 and is available only to deputized Census researchers.

[22] I list this data through 2004 since that is the last year with flow data matched to March 2005 firm and establishment count data.

economy. Ordinary capital grew from $90,359 to $96,459 per worker, or about 1.1% per year on average. IT capital per worker grew at 10.1% per year during this same period, from $6,426 to $11,438 in constant dollars. Note that this period includes the bursting of the "technology bubble." Much of this constant-dollar increase was due to quality adjustments in processing speed and capacity of computing, as Moore's law continued to hold.

Econometric Model

Entry and Expansion

This paper examines how changes in capital intensity affect the dynamics of entry and expansion for both small and large firms. I base my analysis on the establishment births at the industry level. Table 3, based on published data from the SBA, displays national data on establishment openings. According to Line 3 of the table, 768,420 establishments opened in 2004. Line 1 denotes that 644,122 of them, or about 81.7%, represented firm births. Line 2 denotes that the other 124,298 establishment openings represented existing firms that opened a new branch, plant, or store in a secondary location.

Therefore, even though I can only observe establishment entry and exit for specific industries and not firm entry and exit, I can make some plausible assumptions to relate establishment openings to firm entry and expansion.[23] First, looking at the column of firms with 1-4 people, I note that 99.97% of establishment births represent firm births. This makes sense: One wouldn't expect that many businesses of less than five people would open second establishments. By combining the published data for firms of 1-4, 5-9, and 10-19 employees, I

[23] Using public data, I cannot directly observe if an establishment opening by a large firm in industry 2 comes from a firm operating in industry 1 that opens a new establishment in industry 2, or whether it is from a firm already in industry 2 that expands by opening another establishment. Nor can I directly observe a firm birth at the detailed industry level (but I can at the sectoral and national level).

note that of the 616,651 establishments that were opened by firms of less than 20 employees, 616,019 of them—or more than 99.9%—represented new firm births. Therefore, I assume that any establishment birth by a firm of this size is a new firm entering the industry.

I can make a similarly plausible assumption about large firms based on Table 3. Firms with more than 500 employees opened a total of 102,999 establishments in 2004 (Line 3), and 102,727 of them, or 99.74%, represented firm expansions (Line 2). This is fairly intuitive since one would not find many new firms that grew to 500 people or more within their first year. There were only 272 of these brand new large firms in 2004 (Line 1 in the column of firms with 500+ employees). Therefore, I am going to assume that every establishment opening by a firm of more than 500 people is an expansion by an existing firm either from the same industry or another industry.

Using these assumptions, I relate the establishment birth data to small firm entry and large firm expansion:

Small Firms

I estimate the following models using fixed-effects specifications to analyze the sources of new firm growth in each industry:

$$\ln(small)_{it} = \beta_1 \ln(c+k)_{it} + I_i + T_t + \varepsilon_{it} \tag{2}$$

$$\ln(small)_{it} = \beta_1 \ln(c)_{it} + \beta_2 \ln(k)_{it} + I_i + T_t + \varepsilon_{it} \tag{3}$$

The variable $small_{it}$ represents the number of establishment openings by firms with less than 20 people in industry i at the end of year t.[24] I assume that these small establishments represent new firm births. The constant-dollar capital stock of hardware, software, and communications

[24] I match the measure of firm counts from the Census Bureau of March 12th of one year to the capital stock measurements from December 31st of the previous year.

equipment per firm in year t is represented by c_{it}, and the constant-dollar capital stock of ordinary capital per firm is represented by k_{it}. I include a time-constant dummy variable for each industry, which is represented by I_i. I also include a dummy variable for each year, T_t. I use the natural logarithm of small entrants and capital to examine percentage changes in each variable.

Using a panel estimator, I control for industry-specific heterogeneity and need not be concerned with initial levels of the variables being studied. I am more confident about the estimates using this approach rather than a traditional cross-sectional regression where I would attempt to control for other covariates. A considerable advantage is that I control for the unobserved variables (or ones which would be very difficult to measure) that would affect entry, exit, or the number of firms in each industry.

I examine whether more aggregate capital per firm in an industry discourages entry by small firms. Therefore, I test $\beta_{c+k} = 0$ against the one-sided alternative that $\beta_{c+k} < 0$ from equation (2). In (3), I test $\beta_c = 0$ against the alternative that $\beta_c > 0$, that IT capital allows more small firms to enter markets by reducing fixed costs. In order to measure whether ordinary capital intensity acts as a barrier to entry for small firms, I test $\beta_k = 0$ against the alternative that $\beta_k < 0$.

I examine a similar set of hypothesis using a relative, rather than an absolute, measure of entry. I use $small\_rel_{it}$ as the left-hand-side variable, which represents the number of establishment births that come from firms with less than 20 people, for every 100 establishment births that occur in that industry. As shown in Table 3, small firms (with less than 20 employees) and large firms (with more than 500 employees) accounted for 94% of all establishment openings in the United States from 2004-2005. Thus, a relative measure of entry can provide a better comparison of where establishment growth is coming from—small firms or large firms. Using relative entry of small firms, I test $\beta_c = 0$ against the alternative that $\beta_c \neq 0$. It is unclear *a priori* whether establishment openings will come predominantly from small firms or large expansions as the industry becomes more IT capital-intensive. My hypothesis is that ordinary capital intensity should be associated with less establishment growth coming from small firms, and, thus, I test $\beta_{c+k} = 0$ against the one-sided alternative that $\beta_{c+k} < 0$ and $\beta_k = 0$ against the alternative that $\beta_k < 0$.

Large Firms

Among large firms, the variable $large_{it}$ represents the number of establishment births that come from firms with greater than 500 employees.

$$\ln(large)_{it} = \beta_1 \ln(c+k)_{it} + I_i + T_t + \varepsilon_{it} \tag{4}$$

$$\ln(large)_{it} = \beta_1 \ln(c)_{it} + \beta_2 \ln(k)_{it} + I_i + T_t + \varepsilon_{it} \tag{5}$$

My hypotheses regarding firm expansion in the face of higher total capital intensity are different than the ones for small firms. In this case, an increase in total capital intensity should be associated with large firms taking a greater share of the market, as higher fixed costs should favor large firms (and thus expansion). Thus, the hypotheses I test are $\beta_{c+k} = 0$ against $\beta_{c+k} > 0$, and $\beta_k = 0$ against the alternative that $\beta_k > 0$. Regarding higher IT intensity and large firm expansion, I test $\beta_c = 0$ against $\beta_c > 0$ to determine whether large firms use IT to better coordinate and thus expand their operations. I also test $\beta_c = \beta_k$ against the alternative that $\beta_c \neq \beta_k$.

As with the case for small firms, I also test relative expansion versus total establishment openings in the industry. The variable I use is $large\_rel_{it}$, which is establishment openings by firms of 500 or more employees per 100 establishment births that occur in that industry. I assume that these large births represent expansions of existing firms. My hypotheses and alternatives about total and ordinary capital are the same. However, I test $\beta_c = 0$ against the alternative that $\beta_c \neq 0$ because it is an open question as to whether establishment openings would, on net, come from the large firms or small firms.

Turnover

To further complete the picture of how IT has changed the dynamics of entry in the U.S. economy, I examine turnover in addition to gross and relative entry. Examining turnover supplements my analysis of entry by including existing firms. I create the variable $turnover_{it}$, which is 100 times the number of establishment births plus establishment deaths, divided by the number of establishments at the beginning of the period. This provides a useful measure of small firm births and deaths because virtually all establishment births and deaths of firms with fewer than 20 employees are firm births and deaths.

Industry Concentration

Examining the total number of firms and their size distribution complements the analysis of entry. I analyze whether capital intensity is related to a shift in the size distribution towards larger or smaller firms. For example, if capital intensity was negatively associated with entry but positively associated with more small firms in an industry, it would be an indication that although conditions in the industry appear to favor small firms, entry is being blocked or otherwise discouraged. I create left-side variables that account for the total number of firms in each size class, and the percentage of firms within them.

By examining the distribution of firm sizes, I can account for establishment reclassification and growth or decline of existing firms. If an establishment changes the majority of its business from one industry to another, then it will not appear as an establishment opening or closing, but will instead appear as a change in the firm and establishment counts at the industry level. Or, if a firm with 19 employees grows to 25, then that firm will disappear from the small firms group (less than 20 employees) within the distribution.

Lastly, I examine the hypothesis that capital intensity is related to industry concentration because capital is substituting or complementing labor (Brynjolfsson, Malone, Gurbaxani and Kambil 1994, p.1631). Using industry value-added as a left hand-side variable, va_{it}, I examine its relationship with IT and ordinary capital intensity. If capital intensity was associated with smaller firm sizes, for example, but there was no relationship between capital intensity and industry value added, then one explanation would be that capital is substituting for labor (Brynjolfsson, Malone, Gurbaxani and Kambil 1994, p.1637).

Results

My results demonstrate that an increase in IT per firm in an industry is associated with both more entry by small firms, and more expansion by large firms (from the same and other industries). In contrast, an increase in ordinary capital per firm is associated with less small firm entry and less large firm expansion. Relatively speaking, large firms open establishments faster than small firms enter as an industry increases its IT intensity. Examining the competitive conditions within the industry, IT is also associated with more turnover of small firms, but more ordinary capital is associated with less small firm turnover. Finally, an increase in IT is associated with more firms in every size class, and a greater percentage of the industry as large firms. Increases in ordinary capital are associated with fewer firms in every size class and industry fragmentation into small firms.

In this section, I examine entry, expansion, turnover, and firm size results. Combining these results, I conclude that small firms are entering more IT intensive industries despite the fact that there is a higher rate of turnover and more of the industry is shifting into large firms. Thus, IT capital intensity does not serve as a barrier to entry for small firms, although ordinary capital intensity does.

Small Firm Entry

An increase in total capital intensity in an industry is associated with less small firms entering the industry, as I hypothesized earlier. This result can be found in Table 4, where I easily reject that $\beta_{c+k} = 0$ against the alternative that $\beta_{c+k} < 0$ (Column 2). Yet the results are markedly different when total capital is disaggregated into IT capital and ordinary capital.

While an increase in ordinary capital serves as a barrier to entry, an increase in IT capital is associated with more entry of small firms. As Column 4 indicates, a 10% increase in real ordinary capital per firm is associated with about 8.3% fewer small entrants. I reject $\beta_k = 0$ in favor of $\beta_k < 0$ at the 1% level of significance. I also reject $\beta_c = 0$ against the alternative that $\beta_c > 0$, and note that a 10% increase of IT capital per firm is associated with a more than 2% increase in small entrants in that industry, holding other types of capital constant.

However, my results indicate that IT capital intensity does not lead to a greater share of all establishment openings coming from small entrants. None of my results in Columns 5-8 are significant even at the 10% level. In other words, there is no significant relationship between capital intensity and the percentage of establishment openings that represent small firm entrants.

This is true with respect to all capital as well as when capital is disaggregated into IT and ordinary capital.

Large Firm Expansion

While I find that an increase in total capital per firm as well as an increase in ordinary capital per firm are strongly associated with less firm expansion, an increase in IT capital per firm is associated with more large firm expansion. In comparing large firm expansion and small firm entry, I find that large firms are expanding at a faster rate than small firms are opening.

Table 5 illustrates these findings. An increase of 10% in capital per firm in an industry is associated with 6.9% fewer establishment expansions (Column 2), while a 10% increase in ordinary capital per firm is associated with 14.2% fewer establishment births by large firms (Column 4). Yet, a 10% increase in IT capital per firm in an industry is associated with 6.1% *more* establishment births by large firms (Column 4). All of these results are strongly significant.

IT capital, as opposed to ordinary capital, is thus uniquely associated with large firm expansion. This expansion comes from 1) firms already in the industry that add another establishment, and 2) firms in other industries that open an establishment in a new industry for the first time. A 10% increase in IT per worker is associated with an increase of 0.7 establishment openings by large firms for every 100 industry establishment openings (Column 8). However, more ordinary capital per firm is clearly not associated with more establishment openings coming from large firms (Column 8). I reject that $\beta_c = \beta_k$ against the alternative that $\beta_c \neq \beta_k$ at the 10% level of significance (with a p-value of 0.0566).

I do not analyze entry and expansion by firms that employ between 20 and 499 people. Even though these firms account for one-third of U.S. employment (Table 6), 94% of establishment openings in the United States occur in firms with less than 20 employees or more than 500 employees (Table 3). Compared to establishment openings by small or large firms, it less clear whether establishment openings by firms between 20 and 499 employees represent firm births or expansions.[25]

Turnover

A useful measure of the competitive environment is establishment turnover, which for small firms almost always represents firm birth and death. (Whereas for large firms, it almost always represents an expansion or closing of secondary locations). As an industry becomes more ordinary capital-intensive, I find that there is less turnover among small firms (Table 7, Column 4). However, as the industry becomes more IT intensive, there is significantly more turnover among small firms (Column 4). Is the same true for large firms? The answer is no, as Columns 5 through 8 indicate that none of the coefficient estimates are significant.

Industry Concentration

An alternative hypothesis concerning IT and small firm entry is the following: Suppose that IT has nothing to do with encouraging small firm entry but that more IT and more small firm entry is a coincidence. There may already be favorable conditions in the industry that are leading to the breakup of the industry into small firms. This might be the reason for small firm entry – i.e., potential entrants observe these favorable conditions towards industry fragmentation and decide to enter. If this were the case, then I would expect that a greater percentage of the firms in an industry to be small as it becomes more IT intensive. Likewise, given that there is

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[25] However, as I note in Table 3, when a firm that employs 20-99 people opens an establishment, it represents a new firm 86% of the time. Similarly, when a firm that employs 100-499 people opens an establishment, it represents an expansion 87% of the time.

less entry by small firms as the industry becomes more ordinary capital-intensive, I would expect that there would be fewer small firms as a share of all firms in the industry.

However, this is not the case. Table 8 (Columns 5-8) indicates that while there are more firms in an industry as it becomes more IT intensive, it is clear that the increase in firms is from the top of the size distribution. Increases in aggregate capital or ordinary capital are clearly associated with fewer firms in each size category, with the most significant decreases coming from large firms. For another perspective, I display firm sizes as a percentage of all firms in Table 9. IT capital is associated with a smaller percentage of firms that are small and a greater percentage that are large (Columns 5-8). An increase in ordinary capital per firm is associated with a greater percentage of the industry as small firms and less of the industry as large firms (Columns 5-8).

I find that IT capital intensity is associated with not only a shift of the industry into larger firms, but also with increases in industry value-added. A 10% increase in IT per firm is associated with 2.4% more industry value-added (Table 10, Column 4). However, a 10% increase in ordinary capital per firm is not associated with a statistically significant reduction in industry value-added (Table 10, Column 4). Therefore one possible explanation for the industry shift into smaller firm sizes could be due to the fact that firms are substituting ordinary capital for labor (Brynjolfsson, Malone, Gurbaxani and Kambil 1994, p.1637).

CONCLUSION

In this paper, I examined whether IT has leveled the competitive playing field between small and large firms in the U.S. economy using three different measures: entry, turnover, and industry concentration. On the first measure, I found that while increasing ordinary capital per firm served as a barrier to entry, increasing IT capital per worker was associated with more entry by small and large firms. I also found that more IT was associated with a greater percentage of establishment openings coming from large firms rather than small firms. On the second measure, I found that while an increase in IT was associated with entry by small firms, there was also more small firm turnover. In contrast, an increase in ordinary capital was associated with less turnover of small firms.

On the third measure, industry concentration, IT intensity was associated with a shift of the industry into larger firms, while ordinary capital intensity was associated with industry fragmentation into smaller firms. Large firms can use IT to coordinate activities among their establishments and compete against small firms in dispersed, geographic markets. When it comes to products and services, a large firm can identify an innovation in a small firm and then use IT to replicate it across its establishments (McAfee 2005; Winter and Szulanski 2001). This reflects the ability of large firms to use IT to create economies of scale and scope. In contrast, there may be less direct competition between small and large firms as an industry becomes more ordinary capital-intensive. Small firms may differentiate themselves with niche products in order to avoid competition with large firms. This is further suggested by my finding that ordinary capital intensity is associated with less turnover of small firms. There is also the possibility that ordinary capital is substituting for labor.

If IT is associated with large firm expansion and entry and more turnover of small firms, then why would there be greater entry by small firms into IT intensive industries? One possibility is that new small firms can use IT to gain market share despite their size. Another possible explanation is that small entrants could be pursuing a buy-out strategy of entering and then hoping to be purchased by a larger firm. Future studies should be conducted with firm-level data to address the motivation behind entry of small firms into IT intensive versus less IT intensive industries.

APPENDIX A. TABLES AND FIGURES

Table 1: Descriptive Statistics of the Sample: 53 industries, 1998-2005 for 371 observations

	Mean	Standard Deviation	Minimum	Median	Maximum
Full-Time Equivalent (FTE) Employees	1,830,954	2,460,264	36,000	792,000	13,667,000
Firms	110,442	196,520	233	26,121	777,664
IT plus Ordinary Capital per FTE, constant 2000 dollars	\$297,581	\$617,410	\$10,406	\$92,649	\$3,954,813
IT Capital (Hardware, Software and Communications Equipment) per FTE, constant 2000 dollars	\$18,610	\$44,431	\$354	\$4,863	\$275,436
Ordinary Capital per FTE, 2000 dollars	\$278,971	\$600,687	\$8,491	\$83,350	\$3,934,032
IT plus Ordinary Capital per firm, constant 2000 dollars	\$19,646,346	\$50,670,096	\$107,701	\$3,466,036	\$367,914,560
IT Capital per firm, constant 2000 dollars	\$1,722,796	\$6,294,435	\$6,411	\$164,604	\$44,464,984
Ordinary Capital per firm, 2000 dollars	\$17,923,548	\$45,426,788	\$93,204	\$3,375,381	\$323,449,536
Establishment births from firms of less than 20 employees	10,601	19,967	14	1,805	98,479
Establishment births from firms of less than 20 employees, per 100 establishment births in the industry	70.5	20.5	2.5	76.5	97.2
Establishment births from firms of 500 or more employees	1,774	3,524	7	198	22,253
Establishment births from a firm of 500 or more employees, per 100 establishment births in the industry	17.5	19.0	0.4	10.3	95.2
Percentage of firms with less than 20 Employees	76.9	15.1	22.1	80.0	95.9
Percentage of firms with 20-99 Employees	14.5	7.3	3.1	15.1	35.8
Percentage of firms with 100-499 Employees	5.0	5.2	0.5	3.6	30.9
Percentage of firms with more than 500 Employees	3.5	5.7	0.1	1.4	36.2
Turnover: Establishment births plus deaths divided by the number of establishments in the initial year – with firms of less than 20 employees	25.5	7.3	14.2	24.5	65.3
Turnover: Establishment births plus deaths divided by the number of establishments in the initial year – with firms of more than 500 employees	17.2	9.0	5.1	15.0	48.8

Table 2: Descriptive Statistics of the U.S. Economy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Totals					**Per Full-Time Equivalent Employee**			
	Value Added	*C+K*	*K*	*C*	*L*	*Value Added*	*c+k*	*k*	*c*
Year	Billions of 2000 dollars	Billions of 2000 dollars	Billions of 2000 dollars	Billions of 2000 dollars	(Millions)	(2000 Dollars)	(2000 dollars)	(2000 dollars)	(2000 dollars)
1998	7,896.0	9,726.9	9,081.1	645.8	100.5	$78,567	$96,785	$90,359	$6,426
1999	8,285.0	10,105.8	9,335.1	770.7	103.2	$80,281	$97,925	$90,456	$7,468
2000	8,614.3	10,513.8	9,596.3	917.5	105.6	$81,575	$99,563	$90,874	$8,688
2001	8,692.5	10,795.1	9,779.7	1,015.5	105.6	$82,315	$102,227	$92,611	$9,616
2002	8,817.1	10,960.4	9,888.9	1,071.5	104.0	$84,780	$105,388	$95,086	$10,303
2003	9,050.9	11,108.6	9,982.3	1,126.3	103.4	$87,533	$107,433	$96,541	$10,893
2004	9,406.6	11,275.2	10,079.9	1,195.2	104.5	$90,015	$107,896	$96,459	$11,438

Column 1. GDP by Industry Accounts, Real Value Added by Industry, Line 2, Private Industries.

Column 2. Capital is total nonresidential equipment plus nonresidential structures for the private sector, converted to constant 2000 dollars.

Column 3. Sum of non-IT equipment and structures, in constant 2000 dollars.

Column 4. Sum of Computers, Software and Communications equipment, in constant 2000 dollars.

Column 5. BEA Table 6.5D, Full Time Equivalent Employees by Industry, Line 3, Private Industries.

Table 3: Establishment Births in 2004 by Firm Size

		Employment Size of the Firm					
	Total	1-4	5-9	10-19	20-99	100-499	500+
1. Establishment birth, original location (new firms)	644,122	493,406	83,008	39,605	25,321	2,510	272
2. Establishment birth, secondary location	124,298	140	158	334	4,245	16,694	102,727
3. Total	768,420	493,546	83,166	39,939	29,566	19,204	102,999
Addenda: New firm birth as a percentage of establishment birth (1)/(3)	81.70	99.97	99.81	99.16	85.64	13.07	0.26

Source: Small Business Administration, Office of Advocacy. Data represents establishment births from March 12, 2004 through March 12, 2005.

Table 4: Small Firm Dynamics as Function of Capital Intensity

	1	2	3	4	5	6	7	8
Dependent Variable	Ln(small)	Ln(small)	Ln(small)	Ln(small)	small_rel	small_rel	small_rel	small_rel
Ln((C+K)/Firm)	-0.416**	-0.540***			1.59	1.57		
	[0.101]	[0.098]			[4.41]	[5.30]		
Ln(C/Firm)			0.131***	0.213***			-0.128	-3.91
			[0.042]	[0.094]			[1.64]	[2.93]
Ln(K/Firm)			-0.752***	-0.830***			1.55	5.16
			[0.114]	[0.126]			[7.07]	[6.89]
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	371	371	371	371	371	371	371	371
R^2	0.071	0.134	0.158	0.199	0.001	0.176	0.001	0.183

Fixed effects estimation, robust standard errors in brackets. Dependent variable for "Small Entry" in Columns 1-4 is the natural logarithm of the number of small establishment openings (from firms with less than 20 employees). Dependent variable for "Relative Small Entry" in Columns 5-8 is the number of small establishment openings (from firms with less than 20 employees) for every 100 establishment openings in the industry.

*Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level. R^2 is for the "within" transformation.

Table 5: Large Firm Dynamics as Function of Capital Intensity

	1	2	3	4	5	6	7	8
Dependent Variable	**Ln(large)**	**Ln(large)**	**Ln(large)**	**Ln(large)**	**large_rel**	**large_rel**	**large_rel**	**large_rel**
Ln((C+K)/Firm)	-0.705**	-0.689**			-4.95	-4.67		
	[0.280]	[0.343]			[4.93]	[6.11]		
Ln(C/Firm)			0.109	0.606***			2.17	7.16**
			[0.102]	[0.226]			[1.74]	[3.16]
Ln(K/Firm)			-1.11***	-1.42***			-10.01	-11.80
			[0.396]	[0.400]			[7.57]	[7.71]
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	371	371	371	371	371	371	371	371
R^2	0.025	0.029	0.043	0.065	0.006	0.045	0.017	0.067

Fixed effects estimation, robust standard errors in brackets. Dependent variable in Columns 1-4 is the natural logarithm of the number of establishment openings from firms of greater than 500 employees. Dependent variable in Columns 5-8 is number of establishment openings from firms of 500 or more employees for every 100 establishment openings in the industry.

*Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level. R^2 is for the "within" transformation.

Table 6: Businesses with Paid Employees on March 12, 2005

Employment size of Enterprise	Firms	Paid Employees
All	**5,983,546**	**116,317,003**
0-4 employees	3,677,879	5,936,859
5-9 employees	1,050,062	6,898,483
10-19 employees	629,946	8,453,854
20-99 employees	520,897	20,444,349
100-499 employees	87,285	16,911,040
500-9,999 employees	16,565	26,548,921
10,000 or more employees	912	31,123,497

Source: Small Business Administration, Office of Advocacy, based on data provided by the U.S. Census Bureau, Statistics of U.S. Businesses.

Table 7: Establishment Turnover as a Function of Capital Intensity

	1	2	3	4	5	6	7	8
Dependent Variable	**Small Turnover**	**Small Turnover**	**Small Turnover**	**Small Turnover**	**Large Turnover**	**Large Turnover**	**Large Turnover**	**Large Turnover**
Ln((C+K)/Firm)	-0.410	0.87			-2.84	-2.41		
	[2.26]	[2.69]			[4.94]	[6.14]		
Ln(C/Firm)			-0.082	6.07***			-2.11	-3.48
			[0.726]	[1.48]			[1.72]	[3.52]
Ln(K/Firm)			-0.296	-4.64***			0.20	0.06
			[3.18]	[2.90]			[7.46]	[7.74]
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Observations	371	371	371	371	371	371	371	371
R^2	0.000	0.090	0.000	0.162	0.002	0.019	0.007	0.023

Fixed effects estimation, robust standard errors in brackets. In Columns 1-4, the dependent variable is 100 times the number of establishment births plus deaths from firms that employ less than 20 people divided by the number of establishments at the beginning of the year in firms that employ less than 20 people. In Columns 5-8, the dependent variable is 100 times the number of establishment births plus deaths from firms that employ 500 or more people divided by the number of establishments in firms that employ 500 or more at the beginning of the year.

*Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level. R^2 is for the "within" transformation.

Table 8: Firm Size as a Function of Capital Intensity

	1	2	3	4	5	6	7	8
Dependent Variable	Ln(firms <20)	Ln(firms 20-99)	Ln(firms 100-499)	Ln(firms 500+)	Ln(firms <20)	Ln(firms 20-99)	Ln(firms 100-499)	Ln(firms 500+)
Ln((C+K)/firm)	-0.465***	-0.514***	-0.668***	-0.986***				
	[0.079]	[0.089]	[0.177]	[0.313]				
Ln(C/Firm)					0.086**	0.221***	0.421***	0.732***
					[0.041]	[0.044]	[0.080]	[0.128]
Ln(K/Firm)					-0.614***	-0.787***	-1.16***	-1.83***
					[0.087]	[0.082]	[0.196]	[0.36]
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	371	371	371	371	371	371	371	371
R^2	0.365	0.288	0.222	0.189	0.446	0453	0.435	0.447

Fixed effects estimation, robust standard errors in brackets. In Columns 1 and 6, the dependent variable is the natural logarithm of the number of firms with at least one establishment operating in that industry. In Columns 2 and 7, the dependent variable is the natural logarithm of the number of firms that employ less than 20 people. In Columns 3 and 8, the dependent variable is the natural logarithm of the number of firms that employ between 20 and 99 people. In Columns 4 and 9, the dependent variable is the natural logarithm of the number of firms that employ between 100 and 499 people. In Columns 5 and 10, the dependent variable is the natural logarithm of the number of firms that employ 500 or more people.

*Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level. R^2 is for the "within" transformation.

Table 9: Percent of Firms in Each Size Group as a Function of Capital Intensity

	1	2	3	4	5	6	7	8
Dependent Variable	**Percent <20**	**Percent 20-99**	**Percent 100-499**	**Percent 500+**	**Percent <20**	**Percent 20-99**	**Percent 100-499**	**Percent 500+**
Ln((C+K)/Firm)	6.35***	-0.119***	-1.89*	-4.33**				
	[3.45]	[0.465]	[1.06]	[2.11]				
Ln(C/Firm)					-6.81***	0.802**	1.89***	4.12***
					[1.56]	[0.346]	[0.52]	[1.00]
Ln(K/Firm)					13.38***	-0.868	-3.84***	-8.67***
					[4.29]	[0.553]	[1.37]	[2.69]
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	371	371	371	371	371	371	371	371
R^2	0.092	0.158	0.088	0.093	0.255	0.176	0.209	0.265

Fixed effects estimation, robust standard errors in brackets. In Columns 1 and 5, the dependent variable is number of firms that employ less than 20 for every 100 firms in the industry. In Columns 2 and 6, the dependent variable is number of firms that employ between 20 and 99 people for every 100 firms in the industry. In Columns 3 and 7, the dependent variable is number of firms that employ between 100 and 499 people for every 100 firms in the industry. In Columns 4 and 8, the dependent variable is number of firms that employ 500 or more people for every 100 firms in the industry.

*Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level. R^2 is for the "within" transformation.

Table 10: Industry Value-Added as a Function of Capital Intensity

	1	2	3	4
Dependent Variable	**Ln(VA)**	**Ln(VA)**	**Ln(VA)**	**Ln(VA)**
Ln((C+K)/Firm)	0.152*	0.079		
	[0.091]	[0.118]		
Ln(C/Firm)			0.146***	0.238***
			[0.031]	[0.053]
Ln(K/Firm)			-0.121	-0.169
			[0.142]	[0.138]
Year Dummies	No	Yes	No	Yes
Observations	371	371	371	371
R^2	0.016	0.083	0.087	0.140

Fixed effects estimation, robust standard errors in brackets. Dependent variable is the natural logarithm of industry value added.

*Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level. R^2 is for the "within" transformation.

Appendix B. Data Sources

Industries

I begin with the 63 BEA industries that the Bureau of Economic Analysis uses to report industry-level data, and condense them to 56 industries due to reconciling differences in reporting among various data sources. I then drop three IT-producing industries to arrive at a total of 53.

I do not use data for the following industries: Farms (NAICS 111 and 112) and Railroad Transportation (NAICS 482) because they are not measured in the establishment or firms count data. I aggregate the detailed industries in the Information Sector (NAICS 51) to the sector level, due to a change in the industry codes in 2003. This is to preserve consistency between the BEA Fixed Assets data (measured using 1997 NAICS codes) and Census firm size data (which uses 2003 NAICS for 2003-2005). I drop Federal Reserve Banks (NAICS 5210), because I focus on the private business sector. I also combine Hospitals (NAICS 622) and Nursing and Residential Care Facilities (NAICS 623) into one industry because the BEA aggregates them to report industry value-added.

I further narrow the sample to 53 IT-using (or non-IT producing) industries by dropping Computer and Electronic Products (NAICS 334), Computer Design and Related Services (5415), and Information (NAICS 51). Ideally, I would drop the IT-producing industries of Software Publishers (NAICS 5114) and Information and Data Processing Services (NAICS 514) instead of the entire Information sector (NAICS 51). In 2003, detailed Information industries (at the 3 digit NAICS level) were completely reclassified within the NAICS system, making it impossible to match the public data before and after the change. Therefore, I aggregated the industries to the

2-digit sector level (NAICS 51), which could be smoothly matched across all the years in the sample.

Industries used in this analysis appear in Table B.1:

Table B.1: BEA Industries Used in this Analysis

INDUSTRY TITLE (1997 NAICS-based)	1997 NAICS Codes
1. Forestry, fishing, and related activities	113-115
2. Oil and gas extraction	211
3. Mining, except oil and gas	212
4. Support activities for mining	213
5. Utilities	22
6. Construction	23
7. Wood products	321
8. Nonmetallic mineral products	327
9. Primary metals	331
10. Fabricated metal products	332
11. Machinery	333
12. Electrical equipment, appliances, and components	335
13. Motor vehicles, bodies and trailers, and parts	3361-3363
14. Other transportation equipment	3364-3369
15. Furniture and related products	337
16. Miscellaneous manufacturing	339
17. Food, beverage, and tobacco products	311,312
18. Textile mills and textile product mills	313,314
19. Apparel and leather and allied products	315,316
20. Paper products	322
21. Printing and related support activities	323
22. Petroleum and coal products	324
23. Chemical products	325
24. Plastics and rubber products	326
25. Wholesale Trade	42
26. Retail Trade	44-45
27. Air Transportation	481
28. Water transportation	483
29. Truck transportation	484
30. Transit and ground passenger transportation	485
31. Pipeline transportation	486
32. Other transportation and support activities	487,488,492
33. Warehousing and storage	493
34. Credit intermediation and related activities	522
35. Securities, commodity contracts, and investments	523
36. Insurance carriers and related activities	524
37. Funds, trusts, and other financial vehicles	525
38. Real estate	531
39. Rental and leasing services and lessors of intangible assets	532,533
40. Legal services	5411
41. Miscellaneous professional, scientific, and technical services	541 excl. 5411,5415
42. Management of companies and enterprises	55
43. Administrative and support services	561
44. Waste management and remediation services	562
45. Educational services	61
46. Ambulatory health care services	621
47. Hospitals and Nursing and residential care facilities	622,623
48. Social assistance	624
49. Performing arts, spectator sports, museums, and related activities	711,712
50. Amusements, gambling, and recreation industries	713
51. Accommodation	721
52. Food services and drinking places	722
53. Other services, except government	81

Firm Size and Establishment Births and Deaths:

This data was downloaded from the U.S. Small Business Administration, Office of Advocacy web site: http://www.sba.gov/advo/research/data.html. Data for firm sizes was downloaded from http://www.sba.gov/advo/research/us98_02n97.txt and http://www.sba.gov/advo/research/us03_05n02.txt. Data for establishment births and deaths was downloaded from http://www.sba.gov/advo/research/dyn_us_98_05n4.txt.

Below, I reprint the Census Bureau definitions of establishments and paid employment. Those are from http://www.census.gov/epcd/susb/introusb.htm and http://www.census.gov/csd/susb/defterm.html.

Establishments

"An establishment is a single physical location at which business is conducted or services or industrial operations are performed. It is not necessarily identical with a company or enterprise, which may consist of one or more establishments. When two or more activities are carried on at a single location under a single ownership, all activities generally are grouped together as a single establishment. The entire establishment is classified on the basis of its major activity and all data are included in that classification.

An establishment with 0 employment is an establishment reporting no paid employees in the mid-March pay period, but paid employees at some time during the year."

Employees

"Paid employment consists of full- and part-time employees, including salaried officers and executives of corporations, who are on the payroll in the pay period including March 12. Included are employees on paid sick leave, holidays, and vacations; not included are proprietors and partners of unincorporated businesses."

Establishment Births

"Births are establishments that have zero employment in the first quarter of the initial year and positive employment in the first quarter of the subsequent year."

Establishment Deaths

"Deaths are establishments that have positive employment in the first quarter of the initial year and zero employment in the first quarter of the subsequent year."

Industry Classification

"Industry is assigned on an establishment by establishment basis. An enterprise with establishments in more than one industry is counted as a firm in each industry in which it operates an establishment. Nonetheless, as noted above, the employment size category is assigned based on employment in the entire enterprise."

"A firm is defined as that part of an enterprise tabulated within a particular industry, state or metropolitan area. For example, an enterprise with establishments in more than one state would be counted as a firm in each state in which it operates an establishment, but is also counted as only one firm in national all-industry tabulations. Thus, summing the firms across areas or industries would overstate the number of unique firms. Employment size is determined only for the entire enterprise. Hence, counterintuitive results are possible, for example, only 100 employees in a category of firms with 500 employees or more in a particular state."

"Industry is assigned on an establishment by establishment basis. An enterprise with establishments in more than one industry is counted as a firm in each industry in which it operates an establishment. Nonetheless, as noted above, the employment size category is assigned based on employment in the entire enterprise."

Capital Stocks

This data comes from the BEA Detailed Fixed Assets Tables. The two tables are called "Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets" and "Chain-Type Quantity Indexes for Net Capital Stock of Private Nonresidential Fixed Assets." For IT equipment, I combine three categories: 1) Computers and Peripherals, 2) Software, and 3) Communications Equipment.

I convert nominal quantities to constant-dollar (2000 dollars) in the following fashion: I take the current-cost estimate of each capital stock in 2000, and then multiply that value by the value from the quantity index table (in which all real quantities are expressed as 2000=100). This will yield values in constant 2000 dollars. I do this separately for equipment, structures, and the three types of IT equipment listed above for constant dollar estimates. Non-IT equipment is expressed as the difference between all equipment and the three types of IT equipment.

Industry-Level Employment

This data comes from BEA National Income and Products Account Table 6.5D, "Full-Time Equivalent Employees by Industry." It is defined as the number of full-time employees in the industry, plus the number of part-time employees (that are converted to a full-time basis). This table is available at: http://bea.gov/national/nipaweb/TableView.asp?SelectedTable=186&Freq=Year&FirstYear=2006&LastYear=2007.

References

Arrow, K.J. 1974. *The Limits of Organization*. Norton, New York.

Autor, D.H., F. Levy, R.J. Murnane. 2002. Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank. *Industrial & Labor Relations Review*. **55**(3) 432-447.

Bain, J.S. 1956. *Barriers to New Competition*. Harvard University Press, Cambridge, MA.

Bartel, A.P., C. Ichniowski, K. Shaw. 2007. How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills. *Quarterly Journal of Economics*. **122**(4) 1721-1758.

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

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

Brynjolfsson, E., L.M. Hitt, S. Yang. 2002. Intangible Assets: Computers and Organizational Capital. *Brookings Papers on Economic Activity*(1) 137-198.

Brynjolfsson, E., T. Malone, V. Gurbaxani, A. Kambil. 1994. Does Information Technology Lead to Smaller Firms? *Management Science*. **40**(12) 1628-1644.

Brynjolfsson, E., A. McAfee, M. Sorell, F. Zhu. 2007. Scale Without Mass: Business Process Replication and Industry Dynamics. *Harvard Business School Technology & Operations Mgt. Unit Research Paper No. 07-016.* Cambridge, MA.

Burgess, S. 2002. *Managing Information Technology in Small Business: Challenges and Solutions*. Idea Group Publishing, Hershey, PA.

Coase, R.H. 1937. The Nature of the Firm. *Econometrica*. **4**(16) 386-405.

Dierickx, I., K. Cool. 1989. Asset Stock Accumulation and Sustainability of Competitive Advantage. *Management Science*. **35**(12) 1504-1511.

Dixit, A., B. Nalebuff. 1991. Making Strategies Credible. R. Zeckhauser, ed. *Strategy and Choice*. MIT Press, Cambridge, MA, 160-184.

Gibbons, R. 2005. Four Formal(izable) Theories of the Firm? *Journal of Economic Behavior & Organization*. **58**(2) 200-245.

Grossman, S.J., O.D. Hart. 1986. The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration. *The Journal of Political Economy*. **94**(4) 691.

Hall, R.E., S. Woodward. 2007. The Incentives to Start New Companies: Evidence from Venture Capital. *NBER Working Paper #13056*. Cambridge, MA.

Hannan, M.T., J. Freeman. 1977. The Population Ecology of Organizations. *The American Journal of Sociology*. **82**(5) 929-964.

Hannan, M.T., J. Freeman. 1984. Structural Inertia and Organizational Change. *American Sociological Review*. **49**(2) 149-164.

Hart, O., J. Moore. 1990. Property Rights and the Nature of the Firm. *Journal of Political Economy*. **98**(6) 1119-1158.

Kogut, B., U. Zander. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*. **3**(3) 383-397.

Leavitt, H.J., T.L. Whisler. 1958. Management in the 1980's. *Harvard Business Review*. **36**(6) 41-48.

Malone, T.W., J. Yates, R.I. Benjamin. 1987. Electronic Markets and Electronic Hierarchies. *Communications of the ACM*. **30**(6) 484-497.

McAfee, A. 2005. *Pharmacy Service Improvement at CVS (A).* Harvard Business School Case Study 606-015, Boston, MA.

Nelson, R.R., S.G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Belkap Press of Harvard University Press, Cambridge, MA.

Porter, M. 1980. *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. Free Press, New York.

Saunders, A., E. Brynjolfsson. 2007. Information Technology, Productivity and Innovation: Where Are We and Where Do We Go From Here? *MIT Center for Digital Business Working Paper No. 231 and Institute for Innovation and Information Productivity Working Paper No. 101*. Cambridge, MA.

Schmalensee, R. 1978. Entry Deterrence in the Ready-to-Eat Breakfast Cereal Industry. *The Bell Journal of Economics*. **9**(2) 305-327.

Schumpeter, J.A. 1942. *Capitalism, Socialism, and Democracy*. Harper & Brothers, New York.

Teece, D.J., G. Pisano, A. Shuen. 1997. Dynamic Capabilities and Strategic Management. *Strategic Management Journal*. **18**(7) 509-533.

Thompson, J.D. 1967. *Organizations in Action: Social Science Bases of Administrative Theory*. McGraw-Hill, New York.

Tirole, J. 1988. *The Theory of Industrial Organization.* MIT Press, Cambridge, MA.

Weill, P., T.W. Malone, V.T. D'Urso, G. Herman, S. Woerner. 2005. Do Some Business Models Perform Better than Others? A Study of the 1000 Largest US Firms. *MIT Center for Coordination Science Working Paper No. 226.* Cambridge, MA.

Williamson, O.E. 1981. The Economics of Organization: The Transaction Cost Approach. *The American Journal of Sociology.* **87**(3) 548-577.

Wilson, R. 1975. Informational Economies of Scale. *The Bell Journal of Economics.* **6**(1) 184-195.

Winter, S.G., G. Szulanski. 2001. Replication as Strategy. *Organization Science.* **12**(6) 730-743.

Zander, U., B. Kogut. 1995. Knowledge and the Speed of the Transfer and Imitation of Organizational Capabilities: An Empirical Test. *Organization Science.* **6**(1) 76-92.

Chapter 3

The Value and Durability of Patents in High-Tech Firms

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This paper is based on joint work with Erik Brynjolfsson and Lorin Hitt.

We use data on publicly traded high-tech companies from 1984-2002 to examine the relationship between the firms' market value and their patent-based intangible assets. We focus on three characteristics of their patent stocks: quality, diversity, and generality. We also examine how the value of the firms' intangibles changes when previous innovation leaders are no longer at the frontier. Our analysis yields three main findings. First, high-tech firms with patents that are cited by a wide variety of other patents in different patent classes are worth significantly more than firms with patents that are cited by a narrow range of patents. Our second finding is that patent generality is especially valuable in periods of change, when firms are no longer at the leading edge of innovation in a particular year. Firms whose patents were highly generalizable did not lose almost any market value despite the loss of their leadership status. However, the firms whose patents were of low or average generality suffered significant declines in market value. Our third finding is that in periods of change, the value of diverse patents across technology categories is positive but not significant and that generality is comparatively more valuable than diversity. These results suggest that patents with the greatest generality allow firms to most easily adapt to the changing technological landscape in times of rapid and potentially disruptive change.

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INTRODUCTION

Most publicly traded companies in the United States have market values that exceed their book values, suggesting the presence of valuable yet uncounted intangible assets. While a company's high market-to-book ratio suggests the *present-day* existence of intangible assets, we cannot predict with any degree of certainty as to the value of those intangibles in the future. For high-tech firms, the ability to continually innovate and adapt to changing market conditions, which one might call a firm's *dynamic capabilities* (Teece, Pisano and Shuen, 1997), is especially crucial given the short cycle times for new product introductions. While it is well documented that R&D and high-quality patents are correlated with significantly higher market value (Hall, Jaffe and Trajtenberg, 2005), the *durability* of this value is an open question. The ability of a firm to maintain sustainable competitive advantage could change dramatically, depending on technological shifts in the industry due to patenting behavior by rivals.

In this paper, we begin by estimating baseline relationships between three characteristics of patent-based intangible assets in high-tech firms and market value: 1) quality, proxied by citations per patent; 2) flexibility, as evidenced by generality; and 3) diversity, as indicated by the number of technology categories of the firm's patent stock. We then analyze the value of generality and diversity in periods of change—specifically, when a firm that was previously at the frontier of innovation has recently declined in its leadership status. We combine *Compustat* data with the NBER patent citations database to create a sample of 9,969 observations consisting of all publicly traded high-tech firms in the United States from 1984-2002 with an R&D stock of at least $1 million, a patent stock of at least 1, and any patenting activity in the previous 5 years.

Similar to Hall, Jaffe, and Trajtenberg (2005), we find that firms with high-quality patents (as measured by forward citations) are worth significantly more than firms with low-quality patents, robust to several different dependent variables and specifications of the estimating equations. We also confirm previous scholarship that diversification as measured by number of business segments is not correlated with additional market value.[1]

Our new findings are as follows: First, high-tech firms with patents that are cited by a wide variety of patents in different patent classes are worth significantly more than firms with patents that are cited by a narrow range of patents. To measure this patent flexibility, we use a generality score for the patent base, a variable between 0 and 1 that measures the shares of different patent classes that cites the firm's patents.[2] Our second finding reveals that patent flexibility is especially valuable for firms when they are no longer at the leading edge of innovation in a particular year. Firms whose patents were highly generalizable did not suffer almost any market value decline despite their the loss of their leadership status. However, the firms whose patents were of low or average flexibility suffered significant declines in market value. This loss of value was also evident in firms that reported multiple business segments or had diverse patent bases. Overall, our results suggest that in high-tech industries, where technology cycle times are short and innovation is especially rapid, the firms best able to withstand the test of time are not the ones with *diverse* technologies, rather it is the firms with the most *flexible* technologies.

The motivation for this work is that current accounting standards are conservative when it

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[1] While Lang and Stulz (1994) and Berger and Ofek (1995) were the seminal papers that documented the diversification discount in each year using static measures to compare single-segment and multi-segment firms, Campa and Kedia (2002) and Villalonga (2004b) find that the decision by a firm to diversify is not necessarily value-destroying by using more advance econometric techniques to consider the firm's decision to diversify (such as fixed effects or instrumental variables). With their methods, the diversification discount disappears.

[2] Patent generality is based on the dispersion of different 3-digit patent classes that cite an originating patent. Generality is the sum of squared shares of 3-digit patent classes in the citations, then subtracted from 1. Patents with all forward citations in one 3-digit patent class will have a measure of 0, whereas patents with citations in many classes will have a measure approaching 1. We use a citation-weighted average of the firm's patents to arrive at a generality score for the firm as a whole.

comes to reporting intangible assets. Firms are required to expense most investments in advertising, R&D, human capital, and organizational capital, which means that spending in these areas is not fully reflected on the balance sheet.[3] This assumes that the value of intangible spending is entirely captured in the current year, and does not translate into future benefits. Thus, examining how well intangibles maintain their value over time (particularly in the face of turbulence) sheds light on the question of whether intangibles should in fact be treated as assets that endure over time.

We focus on patenting activity as a lens through which to analyze the quality, diversity, and generality of intangible assets. Only certain kinds of innovation are patentable, and thus patenting activity is much more important in some industries than in others. In this work, we focus on high-technology firms, where patenting is an important source of intellectual property protection and an indicator of innovation. As compared to firms in any other industry, high-tech firms arguably face the most rapid cycle times and the greatest need to continually innovate, a crucial source of value over time.

A number of scholars have attempted to place a value on uncounted intangible assets, but they have not examined how those assets maintain their value in the face of volatility. Using macroeconomic data, Corrado, Hulten and Sichel (2005, 2009) estimate that business spending on intangibles not counted in U.S. GDP is at least as large as business investment that is counted as part of GDP. They estimate the stock of intangible assets in the United States could be $3.6 trillion, while Nakamura (2001) estimates the stock of intangibles could be as high as $5 trillion (based on different spending data on intangible investment in the United States).

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[3] One of the few exceptions is purchased goodwill, a residual that is listed when a company acquires another company and then lists the difference between what it pays and the target's net assets.

The existing literature using firm-level data has used the concept of market value to calculate the value of the firm's intangibles, based on the underlying theory that the market value of the firm should be equal to the sum of the firm's capital stocks (both tangible and intangible) (Tobin 1969, Hayashi 1982, R. Hall 2000, 2001). Miller (2006) used market value equations to find that firms with a diverse patent base across multiple business segments have significant value. Barth et al. (1998) found that brand value estimates from *Financial World* magazine are significantly and positively related to stock prices and returns. Brynjolfsson, Hitt and Yang (2002) used a market value equation to estimate the value of information technology, and found positive and significant excess value accruing to firms that had high levels of information technology and complementary organizational practices. Saunders (2011) used similar techniques to value IT-related intangible capital by converting direct spending measures on IT-related intangibles into assets and estimating their value in a market-value equation.

Other papers have used Tobin's *q*, the ratio of a firm's market value to the replacement cost of its tangible assets, to estimate the value of intangible assets. Griliches (1981) was the first to empirically use this technique. It has subsequently been used by such scholars as Cockburn and Griliches (1988) and Hall (1993) to measure the value of R&D, and Wernerfelt and Montgomery (1988) to measure firm focus. Hall, Jaffe and Trajtenberg (2005) used Tobin's *q* to measure the value of R&D, patents, and citations. Among other findings, they noted that citations were significantly correlated with higher market value: Controlling for R&D spending and the number of patents, firms in the 95^{th} percentile of citations per patent (20 or more citations) were worth 54% more than firms with the median number of citations per patent (with 5-6 citations). McGahan and Silverman (2006) found that a firm's Tobin's *q* was significantly affected by the patenting activity by other firms. They further demonstrated that whether the effects added to firm value (through positive spillovers) or subtracted from firm value (because of business stealing effects) depended on whether the innovation was by a rival in the same industry or by an entity not in the same industry, as well as whether intellectual property protection in the industry was strong or weak.

We contribute to this literature by examining whether firms with flexible intangible assets (i.e., a general patent base) have more value and maintain that value over time as compared to firms with inflexible intangible assets (i.e., a more specific patent base). We also compare the effects of patent generality and diversity during periods of change, when firms are no longer at the leading edge of innovation in a particular year. The advantage of using detailed patent data is that we can analyze specific details about the nature of a firm's intangibles over and above the aggregate R&D spending reported by the firm that is found in *Compustat*.

The remainder of our paper is organized as follows. The next section outlines our conceptual framework and is then followed by our econometric model. We then describe the data used in this study, follow with our results, and conclude with a summary and implications for future research.

CONCEPTUAL FRAMEWORK

We begin with the following model to describe firm value, first used by Griliches (1981) and later used by Miller (2006) and Hall, Jaffe and Trajtenberg (2005):

$$V_{it} = q_t(A_{it} + \gamma R_{it})^{\sigma} \tag{1}$$

For firm *i* in year *t*, V_{it} represents market value, A_{it} represents the value of the balance sheet assets, and R_{it} represents the value of intangible assets. The term q_{it} represents the market multiple for assets common to all firms, γ represents the scaling factor for intangible assets, and

σ is the scale parameter. Taking the natural logarithm, and assuming that σ is equal to one,[4] we have:

$$\ln V_{it} = \ln q_t + \ln(A_{it} + \gamma R_{it}) \tag{2}$$

Separating A_{it}, we have

$$\begin{aligned}\ln V_{it} &= \ln q_t + \ln\left(A_{it} \cdot (1+\gamma \frac{R_{it}}{A_{it}})\right) \\ &= \ln q_t + \ln A_{it} + \ln(1+\gamma \frac{R_{it}}{A_{it}})\end{aligned} \tag{3}$$

Finally, by moving A_{it} to the left side of the equation and using the identity that Tobin's q is market value divided by the replacement cost of the tangible assets of the firm, we have:

$$\ln V_{it} - \ln A_{it} = \ln(\frac{V_{it}}{A_{it}}) = \ln Q_{it} = \ln q_{it} + \ln(1+\gamma \frac{R_{it}}{A_{it}}) \tag{4}$$

where $\ln Q_{it}$ is the natural log of the firm's Tobin's q, and $\ln q_t$ is the log of the average Tobin's q in each year. A number of papers (e.g., Griliches 1981, Hall 1993, Miller 2006) utilize the fact that $\ln(1+x)$ is approximately equal to x for small x, thus making the last term in (4) approximately equal to $\gamma \frac{R_{it}}{A_{it}}$. However, Hall, Jaffe and Trajtenberg (2005) compute the full semi-elasticity of $\ln(1+\gamma \frac{R_{it}}{A_{it}})$ since R/A, the ratio of intangible assets to tangible assets, has been growing, and thus for high-intangible firms this approximation becomes increasingly inaccurate. They also modified the basic model in equation (1) to account for patents and quality of citations, which becomes:

[4] Which it approximately does in cross-sectional data; see Hall, Jaffe and Trajtenberg (2005, p.23).

$$V_{it} = q_t(A_{it} + \gamma_1 R_{it} + \gamma_2 A_{it}\frac{P_{it}}{R_{it}} + \gamma_3 A_{it}\frac{Cites_{it}}{P_{it}})^{\sigma} \tag{5}$$

where P_{it} is the stock of the firm's patents, and $Cites_{it}$ is the stock of the firm's citations. Taking the log of both sides and rearranging yields:

$$\ln Q_{it} = \ln q_t + \ln(1 + \gamma_1 \frac{R_{it}}{A_{it}} + \gamma_2 \frac{P_{it}}{R_{it}} + \gamma_3 \frac{Cites_{it}}{P_{it}}) \tag{6}$$

We extend this basic model to include generality, as well as loss of leadership status, to test the hypothesis that flexible intangibles are better able to hold their value when the firm is no longer at the technological frontier. Our hypothesis is that the higher the generality of a firm's patent stock, the broader its knowledge base and hence the better able it is to adapt as the rest of the industry innovates in new directions.

ECONOMETRIC MODEL

In order to examine the relationship between the quality, diversity, and generality of patents and how these characteristics interact with external change, we use a number of estimating equations with various forms of Tobin's q as the dependent variable. As a baseline estimate, our first dependent variable is the log of Tobin's q of the firm. We use several specifications that begin with no industry controls and then include finer-grained measures for industry controls (at the 3 and 4-digit SIC industry level). While industry dummy variables can serve as good controls for effects for firms that operate in a single industry, or "pure-play" firms, a number of firms operate in more than one industry and thus are conglomerates.

To account for multi-segment firms, we use a measure of a "chop-shop" Tobin's q (Lang and Stulz, 1994) based on the Compustat Business Segment data. In these estimates, we use the log of the ratio of Tobin's q divided by an imputed value Tobin's q based on the industry segments of the firm. As the benchmark q for each 4-digit SIC code, we use the median q of all pure-play firms in that industry (based on Berger and Ofek, 1995).[5] For the firm as a whole, the imputed q is based on the imputed q from each of its industry segments, weighted by the assets in each industry.[6] For a single-segment firm, imputed q is simply the median q for its industry.

We use both ordinary least squares (OLS) and fixed effects estimates. For slow-changing ratios, such as the ratio of R&D to assets (Hall, Jaffe and Trajtenberg, 2005), fixed effects may bias the coefficients downward in the presence of measurement error (Griliches and Hausman, 1986). Thus, we may expect to see very different estimates for such ratios in fixed effect specifications than OLS specifications. However, we also estimate several nonlinear specifications with categorical variables (such as a firm being in the 50^{th}-80^{th} percentile of citations per patent). Such variables may be subject to less measurement error: For instance, if the ratio of R&D/assets moves from 21% to 25%, that may not represent actual changes in the firm's R&D stock if our assumptions of R&D depreciation and price deflators are not very applicable to the firm. In that case, we would be capturing measurement error rather than true changes in R&D intensity. However, moving from category to category (such as the 50-80^{th}, 80-95^{th} percentile and 95^{th} and above percentile) is a more significant change (at least for those firms not right at the cutoffs). Thus, we can be more confident that we are measuring true economic phenomena rather than noise.

We seek to use a measure for external change that is reasonably exogenous and would capture technological shifts that would specifically affect focal firms at the frontier of

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[5] Using median q rather than mean q is potentially a better indication of a benchmark q, as the distribution of Tobin's q could get quite skewed especially with high-tech firms. Firms with an extremely high q will exert undue influence on the industry average q, but not the median q.

[6] While it would be ideal to use the replacement cost of assets in each segment (Lang and Stulz, 1994), the data limitations in the segment data limit us to using the book value of assets in that segment. This is the standard practice in the literature.

innovation. We choose the frontier firms with high-quality patents because their values are significantly higher than firms with average-quality patents (Hall, Jaffe, and Trajtenberg, 2005). Thus, while they have the most to gain when their patents are at the center of innovation activity in a given year, they stand the most to lose when their innovation is not as central as it once was. Our interest is in examining the potential reduction in market value to these high-performing firms. We begin by examining the patenting activity in a given year and counting the number of citations each firm receives in all patent applications of that year made by other entities (i.e., non-self citations). To adjust for size, we divide the total non-self citations by the patent stock of the firm. We re-rank firms each year and code the top 20% of the sample as at the frontier of innovation in that year. We examine what happens the following year if the firm loses its status at the frontier, by creating a dummy variable equal to 1 if the firm is currently not an innovation leader but had been the previous year. We examine to what extent the diversity and generality of the firm's patents moderate the effects of moving away from the frontier.

DATA

We use publicly traded firms in the United States from 1984-2002 with at least one business segment in high-tech, at least $1 million of R&D stock, a patent stock of at least 1, and any patenting activity in the previous 5 years. The R&D and patent cutoffs are designed for two reasons. The first is to keep the data reasonable—since we use ratios such as patents/R&D, having very low values for the denominators can lead to some extreme and implausible estimates. The second reason is that since our focus is on valuing the firms' patents based on quality, diversity, and generality, and understanding how well patent-based intangible assets respond to technical change in the industry, firms that have very little patenting or R&D activity are likely to have shifts in market value due to reasons other than changes in value of their patent-based intangible assets.

Tobin's q

Tobin's q is constructed using the method in Chung and Pruitt (1994).[7] The numerator is the market value of the firm, computed as the firm's share price (*Compustat* mnemonic PRCC_F) times the number of common shares outstanding (CSHO), plus the value of the firm's preferred stock (PSTK), the book value of long-term debt (DLTT), and the value of the firm's short-term liabilities minus its short-term assets (LCT minus ACT). We divide the market value by the book value of the firm's total assets (AT) and use this value for Tobin's q.

Excess Value

To compute a measure of industry-adjusted excess value, we do the following: For single-segment firms, we take the natural logarithm of the ratio of the firm's q to the median q of other single-segment firms in its industry. If there are less than five single-segment firms at the 4-digit SIC level in that year, we go successively to the 3, 2, and 1-digit SIC level until there are at least 5 firms to generate each industry's benchmark. To compute excess Tobin's q for multi-segment firms, we compute an imputed q for each of the firm's segments. Each segment is assigned the median Tobin's q for single-segment firms in that segment's industry. We then create an implied q for the firm by weighting each of the segment q values by the book value of the assets in each segment. Finally, we take the natural logarithm of the ratio of the firm's q to its imputed q as the measure of excess value.

[7] Chung and Pruitt (1994) find that their approximation of Tobin's q explains *at least* 96.6% of the variability of the Lindenberg and Ross (1981) method to calculate Tobin's q. While the Lindenberg-Ross method is acknowledged to be more accurate, is a significantly more intricate calculation.

The screening criteria in the Business Segment file to create the imputed qs are as follows: We keep all segments that are classified as "business" or "operating" (dropping segments classified by geography, for example). We drop segments classified as reconciliation (if Segment ID, or SID in *Compustat*, is equal to 99), and segments that do not have an SIC code associated with them. Since SIC codes are available on the Compustat Business Segment data in WRDS beginning with 1984, we start with that year. We drop any firms that have any segments in the financial sector (SIC 6000-6999), since Tobin's q is fundamentally different for these firms (Berger and Ofek, 1995). We also drop firms with negative market value, segment assets, or total firm assets. Finally, we drop those segments that are the only ones operating in a 4-digit SIC in a given year, and we drop those firms that are the only ones operating in a 4-digit primary SIC in a particular year.

Research and Development (R&D) Stock

For each firm, we create annual R&D stocks using the perpetual inventory method (PIM). We start with the first year when the firm begins reporting R&D spending, commencing with 1959 and assuming an infinite service life.[8] We convert all R&D current-dollar spending flows into constant dollars using the BEA price deflator for R&D.[9] Following BEA practice (as well as Hall, Jaffe and Trajtenberg, 2005; Villalonga 2004c), we apply a 15% depreciation rate to R&D.[10] Since companies are required to report R&D spending if it exceeds 1% of sales (Zhao 2002), we assume a value of 0 for that year's R&D spending when it is not reported. Following

[8] Given our depreciation rate of 15% per year, R&D spending in a given year is 96% depreciated after 20 years.

[9] Source: Table 4.1, "Aggregate Input Price Indexes for R&D Investment, 1959-2007," line 10, Private Business. Available at http://www.bea.gov/national/rd.htm.

[10] The BEA uses 15% for all firms except for the following three industries: 18% for firms in Transportation and Warehousing; 11% for Chemicals; and 16.5% for firms in Computers and Electronics. However, to be consistent with Hall, Jaffe and Trajtenberg (2005) as well as with our depreciation rate for patents, we use 15% across the board for all firms. Since our main dependent variable is excess value Tobin's q relative to the firm's industry, we do not expect much distortion using 15% instead of 16.5%.

BEA practice, we assume R&D spending is done at the halfway point in the year, and thus one-half of a year's depreciation is applied to each year of R&D spending before being added to R&D stock. Finally, we convert the constant-dollar R&D stocks back to current-dollar values using the same BEA price deflator.

Brand Stock

Similar to how we calculate R&D stock, we use the perpetual inventory method to aggregate advertising spending in each year as reported by the company, beginning with 1959. To convert the nominal spending data into constant dollars, we create a composite advertising price index from 1959-2002 based on combining three underlying price indices from different years. For 1995 and afterwards, we use the Producer Price Index for advertising from the Bureau of Labor Statistics (BLS).[11] For 1977-1994, we use the BEA Gross Output Price Index for Miscellaneous Technical Services (the finest level of detail which includes the advertising industry). For 1959-1976, we use the BEA Gross Output Price Index for Professional, Scientific, and Technical Services (also the finest level of detail which includes the advertising industry during that period). We use a 45% rate of depreciation for brand (based on Hirschey and Weygand 1985; Villalonga 2004c), assume each year's worth of spending gets half a year's worth of depreciation, and also use an infinite service life.[12] Firms are required to disclose advertising spending if it is material and thus we use a value of 0 for advertising spending if not reported. We then convert the constant dollar values of brand stock back to current-dollars, using the composite price index based on the different series as described above.

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[11] The data series is called PCU541810541810. We use the December values of the "Not seasonally adjusted" series.

[12] Thus, $1 of constant-dollar advertising spending after 7.5 years worth of depreciation has lost approximately 99% of its value.

Patents

Our patent-based measures, which include patent counts, citations, and measures of generality, are from the NBER Patent Citations Data File.[13] The data includes more than 3 million patents granted between 1963-2006, with citations data beginning in 1976. (A thorough description can be found in Hall, Jaffe and Trajtenberg, 2001.) The NBER Patent Citations Data File matches each patent granted in the United States to its assignee, or in about 2% of cases, to multiple owners.[14] The data file matches patents belonging to publicly traded companies to their corresponding GVKEY identifiers in *Compustat* and takes into account the fact that publicly traded firms will acquire patents under a number of different assignee names (either as subsidiaries, or because of misspellings and abbreviations), as well as changes in GVKEY over time because of firm reorganization.[15]

In keeping with the literature (Hall, Jaffe and Trajtenberg 2005, and others), we base the patent stock according to *application* years rather than *grant* years. The average lag time from patent application to grant is about 2 years, and it is reasonable to assume that the knowledge provides benefit to the firm from the time it is produced, rather than 2 or more years later when the patent is granted. Since patents in the United Sates are granted based on the first-to-file rule, the application date is as close as possible to when the new knowledge was produced. Because patents provide intellectual property protection for 20 years,[16] we base our patent stock on the

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[13] Available at https://sites.google.com/site/patentdataproject/Home. Earlier versions of the data can be found at http://www.nber.org/patents/ and Bronwyn Hall's website, http://elsa.berkeley.edu/~bhhall/.

[14] In the few cases where a patent has more than one assignee, we divide the patent and citation counts by the number of assignees. For example, if a patent is granted to two different assignees, each assignee is assigned 0.5 patents, and the forward citations are split evenly between the two.

[15] Hall, Jaffe and Trajtenberg (2001) note that IBM appears in at least 100 different assignee names such as IBM, International Business Machines, Int'l Business Machines, etc.

[16] The 20-year protection period pertains to patents applied for on or after June 8, 1995. For patent applications before that date, it is the greater of either 17 years from the grant date, or 20 years from the filing date.

previous 20 years of patent applications, with each year's patent counts depreciated at a rate of 15% per year for all firms.

Citations

We use the number of forward citations for each patent through 2006 as a proxy for patent quality. To construct citation stocks for each firm, we use the method in Hall, Jaffe and Trajtenberg (2005). A numerical example would be as follows: Suppose a firm applies for a patent in 1990, and after it is granted, receives 30 forward citations until the end of 2006. All 30 citations are added together and thus the firm's citation stock is 30 in 1990.[17] This stock is then depreciated by 15% per year until the end of 2006, at which point it would be equal to 2.2.

Although the patent data continues through 2006, we end our analysis with 2002 for two reasons. The first is because of citation truncation, as it takes a number of years for a patent to build up citations – even blockbuster patents granted in 2006 will likely have very few citations by the end of 2006. However, truncation can be an issue to some extent for any patent,[18] and so Hall, Jaffe and Trajtenberg (2001) develop a model that accounts for any truncation by estimating a deflator to apply to patents in different years to make citation counts comparable. The model takes into account that some fields (such as computers and communications) tend to gather more citations than do other fields (such as chemicals). We use the deflators that are included in the NBER Patent Citations Database to adjust citations accordingly.

The other reason for ending in 2002 is that the patent database includes all patents that were *granted* through the end of 2006. Thus, any patents that were applied for, but not yet granted, before December 31, 2006, are not in the dataset. Four years is a suitable amount of

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[17] The assumption is that a patent is most valuable when it is newly created, which in this hypothetical case is 1990.

[18] Hall, Jaffe, and Trajtenberg (2001) use a 35-year simulated citation lifetime for patents, although they note that a handful of patents are cited *150 years* after being granted.

time between patent applications and patent grants since the average grant time for a patent is 2 years, and about 98% are granted within 4 years (Hall, Jaffe and Trajtenberg 2001, p.47).

Generality

Patent generality is based on the dispersion of different 3-digit patent classes by patents that cite an originating patent, constructed as the following (Hall, Jaffe and Trajtenberg 2001, p.21):

$$G = 1 - \sum_{j}^{n_i} s_{ij}^2 \qquad (7)$$

where s_{ij} represents the percentage of citations received by patent i that belong to patent class j, out of the n_i different patent classes that cited patent i. Patents cited in a wide variety of classes will have a generality score that approaches 1, whereas patents cited by other patents in only one technology class will have a score of 0.

Because this measure can be biased for patents with a small number of citations (Hall, Jaffe and Trajtenberg 2001, pp.44-46), we adjust generality as the following:

$$\hat{G} = \left(\frac{cites}{cites - 1}\right)\left(1 - \sum_{j}^{n_i} s_{ij}^2\right) \qquad (8)$$

We weight the generality score for each patent by its depreciated citation total to create the generality score for the entire firm.

Loss of Leadership

We analyze all backward citations from USPTO patent applications made in each year by companies in our sample. We aggregate all non-self citations to up to 20 previous years of patents owned by sample companies for each application year. The following, for example, is how we construct the measure for IBM in 1984. In that year, there were 67,096 patent applications made to the USPTO by individuals, corporations, universities, governments, and nonprofits, both foreign and domestic. There were 227,667 backward citations by the 1984 applications made to all patents granted since 1976.[19] We match citing-cited pairs[20] to ownership data. Of the 227,667 citations made in that year, 2,789 were to IBM patents from non-IBM patent applications—the most non-self citations of any publicly traded company in that year.[21] We then divide 2,789 by the number of patents in IBM's patent stock, which in 1984 was 3,332.6. Thus, IBM would have approximately 0.837 non-self-citations per patent in 1984. We rank firms each year and code the top 20% of the high-tech sample as at the frontier of innovation in that year. A loss of leadership is a dummy variable equal to 1 if the firm is not in the top 20% but had been in the previous year.

Sample Construction

We begin with all publicly traded nonfinancial companies in *Compustat*, and keep firms that do not have missing values of year, assets, market value, and sales. We drop firms whose primary industry code makes them the only publicly traded firm in their 4-digit SIC. We also drop a small number of GVKEYs that the NBER patent citation database has identified as a secondary identifier for the firm. We start with 1984, the first year in which historical SIC codes are available on *Compustat* at the segment level, and end in 2002, because of the truncation and grant lag issues described above. After calculating excess value using the business segment data,

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[19] Because citation data starts in 1976, if a patent from 1984 cited a patent from 1960, then that citation link would not be recorded. Early years of our sample then do not have as many years to measure citations as, for instance, 2002, which would have more than 25 years. However, patents in computers and communications receive approximately half their citations after 8 years (Hall, Jaffe and Trajtenberg 2001, p.53), so even the earliest sample years will have usable data. More work needs to be done to determine how many years back constitutes a useful measure of the technological frontier of a firm's patents.

[20] That is, each linkage of the 67,096 citing patents to the 227,667 cited patents.

[21] Another 616 citations were made by IBM patent applications to previous IBM patents, for a total of 3,405 citations made to IBM patents from all sources in 1984.

we drop firms with less than $1 million in R&D, a patent stock of less than 1, and no patenting activity in the previous five years, leaving us with a sample of 9,969 firm-years of data.

RESULTS

Our results include a detailed analysis of the dataset; the relationship between the quality, diversity, and generality of patent-based intangibles and market value; and the durability of patents in the face of technical change. We first compare measures of diversification using the reported number of business segments with measures based on patent data. While only one-quarter of the observations report being diversified into more than one business segment, patenting activity reveals potentially far more diversification than what is actually reported. Depending on the assumptions used, 60-87% of the observations could be considered diversified. We find that using either business segments or technology categories of patents, high-tech firms are becoming more focused rather than diversified over the sample period of 1984-2002. We also observe that single-segment or single-technology firms are consistently correlated with a higher average and median Tobin's q than multi-segment or multiple-technology firms.

Our baseline estimates relating Tobin's q and excess value based on segment data indicate that R&D, patents, and citations are all correlated with higher market value, either in OLS or fixed effects specifications. While multi-segment firms are correlated with significantly less value than single-segment firms (or not significantly different from zero), we have conflicting results on the value of diversification for multi-technology firms. In OLS specifications, multiple technology categories are correlated with either zero or positive value, whereas in fixed-effects specifications, firms that add more technology categories are correlated with significantly less value than focused firms in one category.

We then examine how nonlinearities in three aspects of the firm's patent-based intangibles—quality, diversity, and generality—relate to market value. Similar to Hall, Jaffe and Trajtenberg (2005), we find that large and significant market premiums are associated with firms with high-quality patents. In terms of patent diversity, our results in nonlinear specification are similar to our earlier results: While the most diversified firms based on the number of technology segments are correlated with the largest market values in our OLS specifications, in fixed effects specifications very diversified firms are correlated with large, negative, and significant decreases in market value. While there is no significant relationship between patent generality and market value in the linear specifications, nonlinear specifications for patent generality reveal important effects at the ends of the distribution: Firms with highly general patents (in the 90^{th} percentile and above) are correlated with higher value than firms at any other level of generality in their patent base. Moreover, firms with an average level of generality (33^{rd}-66^{th} percentile) are correlated with lower value than both firms with narrow patents (0-10^{th} percentile) and firms with highly general patents in virtually every specification.

Finally, we find that flexible intangibles (i.e., general patents) maintain their value in periods of change better than inflexible patents (patents of low generality), when firms at the innovation frontier are no longer at the forefront of that year's patenting activity. Losing technical leadership is correlated with a significant loss of market value (13-30% in our main specifications) for firms with a low or average level of generality of their patents, whereas firms with the most general patents lost almost no or very little value. Technical diversity, however, did not moderate the loss in market value the way that flexibility did. During periods of change, we find that the value of diverse patents across technology categories is positive but not significant and that generality is comparatively more valuable than diversity. This suggests that flexibility of patents is valuable by enabling firms to adapt to technical change in high-tech industries.

We will now provide a detailed description of each table that covers the aforementioned results. In Table 1, we list sample statistics, and in Table 2, we tabulate the number of reported business segments. Almost three-quarters of the observations in our sample are single-segment firm-years. The majority of firms in our sample are from the manufacturing sector and tend to report less diversification than service-sector firms.[22] Approximately half of the business segments in our sample are from high-tech manufacturing, and the other half come from communications services, software, and computer-related services. In our screening procedure, we include firms with at least one high-tech business segment, resulting in a sample of approximately 80% of business segments being classified as high-tech, and the other 20% being classified outside of high-tech (most of which are in non-high-tech manufacturing).

Villalonga (2004a) observed that business segments are incomplete measures of diversification since they are publicly reported by firms; in fact, most firms that reported as single-segment were actually diversified when using establishment measures from the U.S. Census Bureau. Based on this insight, we use patent data as a way to examine the scope of the firm beyond what business segments would indicate. In Table 3, we divide the patents in our sample according to the knowledge categories as defined by Hall, Jaffe and Trajtenberg (2001). Approximately 80% of the patents and 85% of the citations held by firms in our sample come from the following three fields: *computers and communications*, *electrical and electronic*, and *mechanical*.

[22] Villalonga (2004a, p.482) noted that only 20% of multisegment firms in *Compustat* were manufacturing-only firms.

Using the knowledge subcategories from Table 3 to classify diversification, the majority of firms in our sample would be considered diversified. We list three different measures of diversification in Table 4, which varies by how many years of patenting activity we use. If we use the widest possible measure—utilizing the previous 20 years of patenting activity—only 13% of firms would be classified as "pure-play" firms, meaning that their patents fall within a single knowledge category. If we use a narrower 5-year window, then 22% of the observations would consist of single-technology firms. The most restrictive measure would consider only the current year of patent applications. Even with this high restriction, only 40% of firms-years would consist of a single technology category.[23]

The number of patenting years to consider for the purposes of diversification (as opposed to aggregation for patent stocks) is not entirely straightforward. While SIC industry classification is based on current-year sales of products, patents provide intellectual property protection for up to 20 years. Thus, it is theoretically possible that firms will produce products based on 20-year-old patents. Using current-year patent applications may be too restrictive a measure for the industries the firm can participate in, especially given the lag time for patent applications. However, considering that the sample consists of high-tech firms with short cycle times, we use the previous 5 years worth of patenting activity to measure diversification.

One difficultly with comparing patents to industries is that patent classification is not by industry code and thus there is not a one-to-one correspondence between patent classes and SIC industry codes.[24] However, in terms of measuring diversification, we note that the knowledge

[23] There are fewer observations to consider if we examine patenting activity in the current year. Our main sample as a whole considers firms that patented any time in the last five years.

[24] However, Brian Silverman created a concordance between the International Patent Class (IPC) system and 4-digit SIC codes, which lists a likelihood table relating the probability that a patent in a particular IPC codes would be used by a firm in a 4-digit SIC code.

categories are sufficiently broad to fit into at least one or more SIC industries. For example, while patents in subcategory 23 (*information storage*) would correspond with SIC industry 3572 (*computer storage devices*), patents in subcategory 21 (*communications*) could apply to at least three different manufacturing industries (SIC codes 3661, 3663, 3669) and five different service industries (inside SIC sector 48). If anything, NBER knowledge subcategories are very likely a conservative estimate of diversification as compared to a measure of diversification that would be based on matching patents to 4-digit SIC industries.

Taking Tables 5 and 6 together, we observe a trend towards focus among high-technology firms. This is evident in the decrease in the number of business segments being reported as well as the number of different technologies that are being patented by each firm.[25]

In Table 5, we divide the sample into single- and multi-segment firms. For multi-segment firms, the number of reported business segments and the number of technology categories have trended downward. For single-segment firms, while the median number of technology categories has remained the same since 1988, the average number of technology categories has declined. This suggests that large firms that report as single-segment are becoming more focused. We also note that Tobin's q is higher for single-segment than multi-segment firms in each year, consistent with the diversification discount reported in the literature (Lang and Stulz 1994; Berger and Ofek 1995).[26]

In Table 6, we divide the sample into single-technology firms and multiple technology firms. The average number of business segments for single-technology firms decreased in the late 1980s, and then rose again in the late 1990s. This may be due to the change in reporting

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[25] Using the five years of patenting activity as the measure of technology diversification.

[26] However, more recent literature has noted that diversification is not necessary value-destroying. See note 1.

requirements for business segments in 1998 (from SFAS 14 to SFAS 131), resulting in firms reporting more segments (Berger and Hann, 2003). The number of different technologies for multi-segment firms has been falling, from close to 9 in 1984 to about 7 by 2002. Single-technology firms have consistently higher average Tobin's q, (although the median for single-technology firms was lower than multi-technology firms the late 1980s as well as 2000-2001.)

We estimate the relationship between the firm's intangible assets and Tobin's q in Table 7. We begin with R&D intensity only, and then include more variables such as advertising intensity, patent and citation intensity, patent generality, and diversification (both in business segments or in technology categories).

R&D by itself is correlated with higher market value, although less than existing theory would predict. In column 1, a one percentage point increase of R&D/assets is correlated with 0.136% more Tobin's q (instead of a theoretical value of 1 percent). Once controls for industry are included, the estimate for R&D intensity is lower, although still positive. Why R&D by itself is estimated at less than 1 is interesting. Although Hall, Jaffe and Trajtenberg (2005) estimated a point estimate for the coefficient of R&D/assets of .563 based on a sample of manufacturing firms from 1985-1992, they included all industries while our paper focuses on high-technology firms. Hall (1993) notes that the elasticity of R&D/assets to Tobin's q has fallen considerably in the 1980s. Hall, Jaffe and Trajtenberg (2005) find that from 1976-1984 their point estimate for R&D/assets on log of Tobin's q is 1.754. Our findings for R&D intensity is consistent with the story that R&D spending is necessary to enter high-tech (or other) industries, but purely spending more on R&D than other rival firms does not ensure greater value.

We estimate that each extra patent per million dollars of R&D is worth 2.5%-3.6%, and each additional citation per patent is correlated with about 0.7%-0.9% of market value. While adding industry effects does not diminish the impact of additional patent intensity, industry effects somewhat diminish the coefficient for the value citations. Nevertheless, even in the fixed effects specification in Column 10, patent and citation intensity are still positively and significantly correlated with a higher Tobin's q.

Using the linear specifications in Table 7, we do not find that more general patents are correlated with statistically significant changes in market value. However, given the nonlinear nature of this variable, if high generality and low generality were correlated with changes in market value but average generality was not (i.e., if the relationship between generality and market value were U-shaped or inverse-U-shaped), then we would expect insignificant results from a linear specification.[27] In fact, the nonlinear specifications in Table 11 reveal positive and significant changes to market value at either end of generality (either narrow or very general), which we further elaborate on below.

Finally, we include a dummy variable if the firm reports more than one business segment, and a dummy variable if the firm is diversified in more than one technology area. We find that diversification is associated with a decrease of market value. Using business segments, we replicate the diversification discount documented by Lang and Stulz (1994) and Berger and Ofek (1995). While adding technology diversification in the OLS specifications barely reduces the negative estimates for business segment diversification, the business-segment diversification discount disappears in our fixed-effects specification in Column 10.[28] In fixed effects though, technological diversification is negatively and significantly associated with market value.

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[27] Since the linear specification assumes the same percentage change to the dependent variable for the same amount of change in our independent variables everywhere in the distribution.

[28] Similar to the finding of Campa and Kedia (2002, p.1751) who found that with fixed effects specifications on the business segment data, the diversification discount disappeared.

In Table 8, we use a number of different dependent variables to examine the robustness of the relationship between intangible assets and market value. Our main dependent variable is excess value, which is the log of the ratio of the firm's Tobin's q to its imputed q. Imputed q is the median q of all single-segment firms in the 4-digit SIC code (or the finest level of industry detail that has at least 5 single-segment firms). For a single-segment firm, imputed q is simply the median q for its industry. For multi-segment firms, each segment is assigned the imputed q for its 4-digit SIC code, and then the firm's imputed q as a whole is based on the imputed q from each of its industry segments, weighted by the firm's assets in each segment. For robustness, we estimate models with imputed q based on the average industry q rather than the median (Lang and Stulz 1994; Villalonga 2004a). We also estimate models that drop observations with a log of imputed value of greater than 1.386 or less than -1.386 (Berger and Ofek 1995; Campa and Kedia 2002; Villalonga 2004a), implying an excess value of greater than 400% or less than 25% of its imputed value.

Greater citation intensity is positively and significantly correlated with greater market value in all specifications of Table 8. Greater patent intensity is associated with an increase in market value, although in the fixed effects specifications in Columns 3 and 7 the effects are not statistically significant. Diversification as measured by business segments is not correlated with positive and statistically significant value in any specification, and is often correlated with negative and significant decreases in market value (although in fixed effects, this effect is not significant). In terms of technological diversification, we have conflicting results. Some OLS specifications show a positive correlation between technological diversification and market value, while others show a near-zero correlation. The fixed-effects specifications indicate a negative and statistically significant relationship between technological diversification and

Tobin's q.

Advertising is not associated with a statistically significant change to market value, although in several specifications it is correlated with large and negative point estimates. The most likely explanation is that the value of advertising and thus brand is highly dependent on the firm's industry, and the most brand-intensive industries (such as consumer nondurables) are not in our sample. Many of the high-tech companies in our sample are not final goods suppliers to consumers and are thus less dependent on advertising and brand. The advertising intensity variable is also highly skewed. While the average ratio of advertising assets to total assets is 1.7%, the median in our sample is less than 0.1%.

In Tables 9 and 10, we list the mean and median Tobin's q as well as the number of observations in a number of dimensions: 1) quality, proxied by citations per patent; 2) flexibility, as evidenced by generality; and 3) diversity, as indicated by the number of technology categories of the firm's patent stock.

As we illustrate in Table 9, single-segment firms have a higher Tobin's q than multi-segment firms whether they patent in one technology category or in many. We note that firms with more technology categories are generally correlated with a lower Tobin's q. At the intersection of business segments and number of technologies, the single-technology, single-segment firm combination is correlated with the greatest value. For multi-segment firms, being focused in a single technology category is correlated with the most value, and there is a noticeable dip in value moving from a single technology to two technology categories. There are further decreases for very diversified patent bases (8 technologies and above).

We then subdivide the sample according to different sizes of overall patent stock in each year. The percentiles are 0-50, 50-80, 80-95, and 95 and above. Within each patent stock size category, companies that are more focused in terms of technology categories are generally correlated with more value.[29]

Table 9 further illustrates that at all levels of technological diversity, higher generality of a firm's patent stock is associated with more value. There is also evidence of complementarity—firms with the narrowest patent stocks (low generality) are correlated with the most value when they are also patenting in just one or two technologies. However, firms in the 90th and above percentile of generality are correlated with the most value when they have patent activity in several technologies. Interestingly, firms with a highly diverse set of patents (8 or more technology categories) are not correlated with more value at higher levels of generality.

Patent quality (as proxied by citations per patent) is clearly correlated with higher market value. We divide the sample into four different categories to measure quality by citations per patent: percentiles for 0-50, 50-80, 80-95, and 95 and above. Higher percentile groups are correlated with successively higher levels of Tobin's q. There is evidence of complementarity between citations and technology categories. Firms in the 95th percentile and above for citations per patent are correlated with greater value for 3-7 technologies categories instead of one or two categories. At all other lower levels of cites per patent, there is little additional value (or negative value) correlated with a more diverse patent base.

In Table 10, we examine the interaction between patent generality and business segments, size of patent stock, and citations per patent. Firms with general patents are correlated with higher Tobin's q whether they are single- or multi-segment. At each level of citation intensity, there also tends to be greater value with either narrow or highly generalized patents than with

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[29] As the overall patent stock grows in size, Tobin's q decreases. This is likely correlated with firm size effects, which may indicate the maturity of the markets in which the firm operates. Larger firms grow more slowly than smaller firms, and so this will be reflected in a lower Tobin's q.

patents with an average level of generality.

We then use the categories from Table 10 in multivariate regressions in Table 11. We estimate several different combinations of dependent variables such as the log of Tobin's q or the log of excess Tobin's q, whether we use median or mean q to compute the industry benchmark, whether we drop extreme observations (firms with excess Tobin's q of less than 25% or greater than 400% of the industry), and whether we use OLS or fixed effects.

Our most robust findings concern patent quality. Firms in the 80-95th and the 95th percentile and above in citations per patent are worth significantly more than firms in the bottom 50% of cites/patent, robust to all specifications. In most specifications, the differences in the coefficients for each of the three groups divided by citations/patent are statistically (as well as practically) significant from each other.

In every specification, we estimate that firms with highly general patents (in the 90th percentile and above) are correlated with more value than firms with any other level of generality of their patent base. This is statistically significant in all but two specifications (Columns 3 and 11). This is consistent with previous scholarship. Bresnahan and Trajtenberg (1995) observed that information and communications technologies are "general-purpose-technologies," while Hall, Jaffe and Trajtenberg (2001) noted that of the six major technology fields, patents in the field of computers and communications (Field 3 from Table 3) were the most generalizable (based on an analysis of patent data from 1975-1999).

The correlation between technological diversity and value is dramatically different between the OLS and fixed effects specifications. In OLS, firms with patents in more fields are correlated with higher market value. However, in the fixed effects specifications as well as the OLS specifications where extreme-valued observations are dropped, diversity is negatively and significantly correlated with lower market value. Higher technological diversity could be proxying for the size of the firm and its patent base, which may be why the OLS specifications are so different from those of fixed effects for these variables. The diversity variables were the only ones whose coefficient estimates changed so dramatically by using fixed effects instead of OLS, or by dropping the extreme values of Tobin's q.

In Table 12, we illustrate how external change affects the value of patents, as moderated by the generality and diversity of a firm's patent base. Our results for R&D intensity, advertising, patent intensity, citations, and diversification are largely unchanged from the baseline estimates in Tables 7 and 8. Given that there is a large premium for firms with very high citations per patent, we examine what happens when innovative activity by other firms move in a different direction from leading firms at the frontier.

We examine the patenting activity in a given year and count the number of citations the firm receives in all patent applications of that year from any other source other than the firm itself. In other words, we count the number of non-self-citations to a firm in a given year. To scale this number, we divide it by the patent stock of the firm. Given that different years will have greater citation intensities, we re-rank firms each year and code the top 20% of the high-tech sample as at the frontier of innovation in that year. We analyze what happens the following year if the firm loses its status at the frontier. We create a dummy variable equal to 1 if the firm was an innovative leader in the previous year and then lost its status in the current year. We then examine to what extent the diversity and generality of the firm's patents moderate the effects on market value of losing this status.

In all of our estimates, there is a large, negative effect on market value from receding from the forefront of innovation. This is statistically significant in almost all of our estimates and is robust to fixed effects, use the mean or median q to impute an industry benchmark, or whether we drop firms with extreme values of Tobin's q relative to their industries. Using OLS, we estimate that the direct effect of losing technical leadership is approximately 20-32%. Using the relative excess value to the median of the industry, we estimate a drop from 18-31% using the full sample, or 13-16% using the reduced sample. We interact this loss with characteristics of the firm's intangibles. Being a multi-segment firm is associated with a magnification of this effect (although most estimates are not statistically significant). Being diversified in multiple technologies does moderate the effect somewhat, although most estimates are not statistically significant either.

However, having a patent base with a high degree of generality (in the 66^{th} percentile and above for generality) nullifies the effect almost entirely. This is not the same for firms with narrow patents (generality below the 33^{rd} percentile).

CONCLUSION

In this work, we examined how the value of high-tech firms is related to the quality, diversity, and generality of their patent base, and how this value changes when firms with high-quality patents are no longer at the frontier of innovation. Our results are consistent with the story that R&D is necessary for entry into certain industries, but that high R&D itself does not ensure value. Rather, patent intensity as well as citation intensity are correlated with more value. There are significant premiums of being in the top 5% and 20% of citations per patent. While there is a modest premium to general patents over narrowly focused patents, the value of generality is especially significant when the firm is no longer a leader in a given year's innovation activity. In contrast, the value of diversity is positive but not significant during these periods of change, with generality being comparatively more valuable than diversity. One interpretation of these results is that patents with the greatest generality allow firms to more easily adapt to the changing technological landscape in times of rapid and potentially disruptive change. This is especially true for firms in high-tech industries, where technology cycle times are short and innovation is especially rapid. Future research can examine how other types of external change affects the value of the firm's intangibles so that we can better understand not only the value but also the durability of these assets.

Table 1: Descriptive Statistics of the Sample, 1984-2002

Variable	Mean	Median	Minimum	25th Percentile	75th Percentile	Maximum	Std. Deviation
Market Value	2,494.9	126.1	.008	30.7	689.0	461,178.9	12,878.1
Tobin's *q*	2.21	1.07	.0002	.563	2.18	136.4	4.83
R&D Stock	373.1	31.0	1.00	10.2	110.7	27,796.2	1,628.4
Advertising Stock	22.2	.032	0	0	1.45	5,170.2	164.0
Total Balance Sheet Assets	1,798.1	109.1	.048	34.4	479.7	244,192.5	8,568.0
Patent Stock	146.4	8.69	1	3.35	31.8	11,884.7	685.1
Citation Stock	2,794.0	208.6	0	68.6	722.5	350,486.6	13,119.0
R&D/Assets	.492	.294	<.000	.163	.497	46.89	1.18
Advertising Stock/Assets	.016	<.000	0	0	.017	1.10	.041
Patents/R&D (MM)	.724	.370	<.000	.148	.804	86.7	1.62
Citations/Patent	27.1	19.4	0	12.4	32.7	388.1	26.7
Generality	.572	.587	0	.497	.678	1.00	.162
Non-self-citations in one application year/patent	2.38	1.44	0	.714	2.77	64.8	3.42
Number of Business Segments	1.50	1	1	1	2	10	1.05

For 9,969 observations with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years.

Table 2: Number of Reported Business Segments, 1984-2002

Number of Reported Business Segments	Firm-Years	Percent	Cumulative
1	7,399	74.22	74.22
2	1,114	11.17	85.39
3	811	8.14	93.53
4	411	4.12	97.65
5	143	1.43	99.09
6	49	0.49	99.58
7	21	0.21	99.79
8	15	0.15	99.94
9	4	0.04	99.98
10	2	0.02	100.00
Total	**9,969**	**100.00**	

Table 3: High-Tech Firm Patent Activity by NBER Technology Classification, 1984-2002

Category	Subcategory	Category Name	% of Sample by Patents	% of Sample by Citations
1		**Chemical**	**11.4**	**7.1**
	11	Agriculture, Food, Textiles	0.2	0.0
	12	Coating	1.2	0.9
	13	Gas	0.1	0.0
	14	Organic Compounds	1.2	0.3
	15	Resins	1.3	0.8
	19	Miscellaneous	7.4	5.0
2		**Computers and Communications**	**37.1**	**47.2**
	21	Communications	12.7	15.5
	22	Computer Hardware and Software	11.0	13.8
	23	Computer Peripherals	4.9	6.2
	24	Information Storage	7.3	9.2
	25	Electronic Business Methods and software	1.3	2.5
3		**Drugs and Medical**	**2.9**	**3.9**
	31	Drugs	1.1	0.6
	32	Surgery and Medical Instruments	1.7	3.1
	33	Genetics	0.0	0.0
	39	Miscellaneous	0.1	0.2
4		**Electrical & Electronic**	**32.9**	**30.7**
	41	Electrical Devices	6.9	5.1
	42	Electrical Lighting	2.2	1.4
	43	Measuring and Testing	3.1	2.6
	44	Nuclear & X-rays	1.7	1.2
	45	Power Systems	4.0	3.7
	46	Semiconductor Devices	10.3	13.5
	49	Miscellaneous	4.6	3.2

5		**Mechanical**	**10.3**	**7.5**
	51	Material Processing and Handling	2.6	1.9
	52	Metal Working	2.1	1.5
	53	Motors, Engines, and Parts	0.9	0.5
	54	Optics	2.0	1.7
	55	Transportation	0.6	0.3
	59	Miscellaneous	2.0	1.6
6		**Others**	**5.4**	**3.5**
	61	Agriculture, Husbandry, Food	0.2	0.0
	62	Amusement Devices	0.0	0.1
	63	Apparel & Textile	0.2	0.0
	64	Earth Working & Wells	0.2	0.2
	65	Furniture, House Fixtures	0.3	0.2
	66	Heating	0.4	0.2
	67	Pipes & Joints	0.2	0.1
	68	Receptacles	0.4	0.2
	69	Miscellaneous	3.4	2.3

N = 9,969 observations. The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years.

Table 4: Diversification of Sample based on NBER Technology Subcategories, 1984-2002

	Based on 20 years of Patenting Activity			Based on 5 years of Patenting Activity			Based on Current Year of Patenting Activity		
Tech Categories	Firm-Years	Percent	Cumulative	Firm-Years	Percent	Cumulative	Firm-Years	Percent	Cumulative
1	1,292	12.96	12.96	2,226	22.23	22.23	2,924	38.62	38.62
2	1,381	13.85	26.81	1,848	18.54	40.87	1,441	19.03	59.65
3	1,257	12.61	39.42	1,334	13.38	54.25	794	10.49	68.13
4	979	9.82	49.24	912	9.15	63.40	509	6.72	74.85
5	778	7.80	57.05	690	6.92	70.32	316	4.17	79.03
6	611	6.12	63.18	489	4.91	75.22	232	3.06	82.09
7	458	4.59	67.77	315	3.16	78.38	172	2.27	84.36
8	347	3.48	71.25	229	2.30	80.68	125	1.65	86.01
9	285	2.86	74.11	222	2.23	82.91	111	1.47	87.48
10	238	2.29	76.40	179	1.80	84.70	99	1.31	88.79
11	215	2.16	78.55	157	1.57	86.28	75	0.99	89.78
12	169	1.70	80.25	111	1.11	87.39	71	0.94	90.72
13	192	1.93	82.17	94	0.94	88.33	67	0.88	91.60
14	132	1.32	83.50	73	0.73	89.07	64	0.85	92.45
15	126	1.26	84.76	80	0.80	89.87	62	0.82	93.26
16	116	1.16	85.93	76	0.76	90.63	50	0.66	93.92
17	105	1.05	86.98	64	0.64	91.27	55	0.73	94.65
18	110	1.10	88.08	71	0.71	91.99	48	0.63	95.29
19	78	0.78	88.87	67	0.67	92.66	45	0.59	95.88
20	72	0.72	89.58	82	0.82	93.48	38	0.50	96.38
21	58	0.58	90.17	64	0.64	94.12	43	0.57	96.95
22	71	0.71	90.88	70	0.70	94.82	44	0.58	97.53
23	96	0.96	91.84	60	0.60	95.43	33	0.44	97.97
24	69	0.69	92.94	68	0.68	96.11	37	0.49	98.45
25	67	0.67	93.21	65	0.65	96.76	22	0.29	98.75
26	80	0.80	94.01	55	0.55	97.31	25	0.33	99.08
27	43	0.43	94.44	59	0.59	97.90	22	0.29	99.37
28	80	0.80	95.25	42	0.42	98.32	20	0.26	99.63
29	58	0.58	95.83	37	0.37	98.70	13	0.17	99.80
30	69	0.69	96.52	42	0.42	99.12	10	0.13	99.93
31	80	0.80	97.32	22	0.22	99.34	1	0.01	99.95
32	59	0.59	97.91	17	0.17	99.51	3	0.04	99.99
33	98	0.98	98.90	25	0.25	99.76	1	0.01	100.00
34	39	0.39	99.29	12	0.12	99.88	--	--	--
35	37	0.37	99.66	9	0.09	99.97	--	--	--
36	24	0.24	99.90	3	0.03	100.00	--	--	--
37	10	0.10	100.00	--	--	--	--	--	--
Total	9,969	100.00		9,969	100.00		7,572	100.00	

The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years.

Table 5: Summary of Single-Segment and Multi-Segment Firms in Sample, 1984-2002

	Single-Segment								Multi-Segment							
			Tech Categories		Assets		Tobin's *q*				Tech Categories		Assets		Tobin's *q*	
Year	**Firms**	**Segments**	**Avg.**	**Med.**	**Avg.**	**Med**	**Avg.**	**Med**	**Firms**	**Avg. Segments**	**Avg.**	**Med.**	**Avg.**	**Med.**	**Avg.**	**Med.**
1984	218	1	4.90	2	779.9	48.9	1.35	.77	146	3.40	10.32	7	1,703.4	206.9	.71	.57
1985	241	1	4.88	2	1,008.9	63.4	1.30	.90	140	3.36	9.90	6	1,803.9	197.9	.81	.68
1986	262	1	4.90	2	955.1	62.0	1.44	.84	135	3.41	10.13	7	2,605.6	256.5	.84	.69
1987	275	1	4.97	3	1,149.1	69.4	1.47	.76	114	3.30	10.38	6	3,222.9	243.8	.93	.68
1988	276	1	5.16	3	1,202.7	70.4	1.42	.72	104	3.12	9.99	7	2,502.2	235.5	.86	.68
1989	282	1	5.13	3	1,299.5	77.6	1.26	.70	88	3.00	10.27	7	2,062.6	198.0	.81	.60
1990	277	1	5.11	3	1,255.4	75.4	1.10	.64	85	3.07	10.86	8	2,533.1	319.5	.58	.49
1991	289	1	4.83	3	1,243.9	93.8	1.56	.84	84	3.01	10.99	9	3,228.4	261.2	.73	.61
1992	335	1	4.57	3	1,013.0	64.1	1.50	.92	100	2.96	9.69	6	2,723.8	190.5	.92	.73
1993	392	1	4.51	3	1,001.3	68.1	1.93	1.15	105	2.96	10.36	7	3,242.4	337.1	1.04	.77
1994	405	1	4.75	3	1,054.2	79.7	1.96	1.32	103	2.92	9.93	7	3,282.1	263.2	1.07	.78
1995	468	1	4.77	3	1,212.5	84.3	2.48	1.68	116	2.88	9.07	6	2,749.5	233.3	1.47	1.05
1996	583	1	4.57	3	1,219.2	78.8	2.50	1.52	119	2.80	9.52	6	3,827.9	284.9	1.49	1.07
1997	621	1	4.49	3	1,202.0	80.9	2.48	1.59	112	2.90	10.31	6	5,321.9	376.8	1.66	1.16
1998	505	1	3.95	3	621.2	72.6	3.24	1.37	196	2.72	8.01	4	3,528.0	317.5	1.64	1.12
1999	505	1	3.56	3	1,011.0	82.9	8.02	3.39	213	2.72	8.19	4	4,435.9	341.0	3.50	1.35
2000	519	1	3.73	3	814.3	127.6	3.57	1.76	208	2.77	8.61	4.5	6,444.3	389.2	1.89	1.15
2001	511	1	3.92	3	740.1	124.6	2.28	1.54	205	2.78	9.17	5	6,900.8	506.8	1.41	1.04
2002	436	1	4.27	3	653.8	108.6	1.88	.97	197	2.91	9.27	5	6,808.4	490.0	1.15	.80
Avg.		**1**	**4.48**	**3**	**1,043.7**	**83.1**	**2.50**	**1.21**		**2.97**	**9.51**	**6**	**3,969.9**	**317.8**	**1.37**	**.83**

N = 9,969 observations. The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years.

Table 6: Summary of Sample by Technology Diversification, 1984-2002

	Single-Technology								Multi-Technology							
			Business Segments		Assets		Tobin's *q*				Business Segments		Assets		Tobin's *q*	
Year	Firms	Avg. Tech. Categories	Avg.	Med.	Avg.	Med.	Avg.	Med.	Firms	Avg. Tech. Categories	Avg.	Med.	Avg.	Med.	Avg.	Med.
1984	77	1	1.45	1.00	74.1	28.9	1.20	.71	287	8.74	2.10	1.00	1,443.5	126.3	1.06	.67
1985	95	1	1.33	1.00	346.3	30.9	1.38	.86	286	8.68	2.04	1.00	1,625.7	139.8	1.03	.76
1986	96	1	1.45	1.00	214.9	32.7	1.48	.74	301	8.48	1.94	1.00	1,929.2	140.7	1.16	.77
1987	84	1	1.30	1.00	215.0	29.5	1.77	.67	305	8.09	1.78	1.00	2,177.8	148.7	1.18	.76
1988	80	1	1.25	1.00	198.2	26.2	1.76	.66	300	7.94	1.67	1.00	1,921.1	150.3	1.14	.70
1989	83	1	1.16	1.00	52.0	26.3	1.49	.69	287	7.90	1.57	1.00	1,894.3	147.8	1.05	.68
1990	86	1	1.14	1.00	95.3	32.5	1.12	.64	276	8.16	1.59	1.00	2,010.3	163.5	.94	.56
1991	80	1	1.16	1.00	234.5	29.5	2.18	1.02	293	7.65	1.53	1.00	2,088.4	168.4	1.15	.73
1992	110	1	1.21	1.00	201.1	31.8	1.77	1.11	325	7.32	1.53	1.00	1,805.2	156.2	1.25	.82
1993	114	1	1.10	1.00	192.2	31.1	2.13	1.28	382	7.14	1.51	1.00	1,851.0	141.4	1.64	.96
1994	117	1	1.26	1.00	520.1	37.3	2.31	1.38	391	7.21	1.43	1.00	1,793.5	143.0	1.63	1.07
1995	127	1	1.22	1.00	152.3	42.0	2.83	1.77	457	6.90	1.42	1.00	1,894.5	155.1	2.14	1.43
1996	168	1	1.11	1.00	128.8	46.0	2.64	1.82	534	6.78	1.37	1.00	2,137.4	125.5	2.24	1.38
1997	155	1	1.10	1.00	136.9	41.1	2.51	1.48	578	6.56	1.34	1.00	2,281.9	136.5	2.31	1.53
1998	166	1	1.28	1.00	262.8	45.3	3.59	1.20	535	6.46	1.54	1.00	1,874.9	146.2	2.60	1.29
1999	151	1	1.23	1.00	241.3	57.4	9.21	3.85	567	6.08	1.59	1.00	2,585.6	149.1	5.81	2.13
2000	156	1	1.29	1.00	375.7	76.7	3.44	1.47	571	6.36	1.57	1.00	3,155.0	230.3	2.93	1.52
2001	149	1	1.28	1.00	1,211.4	53.3	2.08	1.17	567	6.60	1.57	1.00	2,875.2	229.4	2.00	1.34
2002	132	1	1.39	1.00	1,179.1	33.4	2.37	1.19	501	7.13	1.64	1.00	3,045.8	237.1	1.45	.87
Avg.		**1**	**1.24**	**1.00**	**344.2**	**38.4**	**2.73**	**1.20**		**7.16**	**1.58**	**1.00**	**2,216.0**	**160.1**	**2.06**	**1.04**

N = 9,969 observations. The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years.

Table 7: Tobin's q as a Function of Intangible Assets, 1984-2002

	(1) OLS Ln(q)	(2) OLS Ln(q)	(3) OLS Ln(q)	(4) OLS Ln(q)	(5) OLS Ln(q)	(6) OLS Ln(q)	(7) OLS Ln(q)	(8) OLS Ln(q)	(9) OLS Ln(q)	(10) FE Ln(q)
R&D/Assets	.136	.133	.134	.126	.126	.119	.120	.116	.115	.089
	(.016)	(.016)	(.016)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.013)
Advertising Stock/Assets		.394	.399	.202	.198	.065	.067	.048	-.107	-.911
		(.584)	(.584)	(.575)	(.574)	(.574)	(.573)	(.591)	(.590)	(.752)
Patents/R&D (MMs)			.029	.030	.030	.030	.030	.034	.036	.025
			(.006)	(.012)	(.012)	(.012)	(.012)	(.013)	(.013)	(.019)
Citations/Patent				.009	.009	.008	.009	.007	.006	.007
				(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Generality					.069	.068	.065	.108	.156	-.093
					(.113)	(.112)	(.114)	(.112)	(.110)	(.153)
Multisegment Firm Dummy = 1						-.232	-.232	-.186	-.140	-.001
						(.042)	(.042)	(.048)	(.049)	(.054)
Technological Diversification = 1							.009	.038	.030	-.133
							(.044)	(.044)	(.043)	(.043)
No Advertising Dummy = 1		.131	.131	.131	.131	.129	.129	.129	.169	.186
		(.046)	(.046)	(.043)	(.044)	(.044)	(.044)	(.044)	(.044)	(.031)
Number of Observations	9,969	9,969	9,969	9,969	9,969	9,969	9,969	9,969	9,969	9,969
R-squared	.128	.131	.132	.177	.177	.184	.184	.218	.356	
Controls	Year	Year	Year	Year	Year	Year	Year	Year	Year	Year
								3-Digit SIC	4-Digit SIC	

The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years. The dependent variable is the log of Tobin's q as measured by Chung and Pruitt (1994). Robust standard errors clustered by firm in parentheses.

Table 8: Different Measures of Excess Value as a Function of Intangible Assets, 1984-2002

	(1) OLS Segment data	(2) OLS Segment data	(3) FE Segment data	(4) FE Segment data	(5) OLS Primary SIC	(6) OLS Primary SIC	(7) FE Primary SIC	(8) FE Primary SIC	(9) OLS Segment data	(10) OLS Segment data	(11) FE Segment data	(12) FE Segment data
R&D/Assets	.113	.013	.088	-.009	.113	.007	.089	.003	.106	.068	.072	.074
	(.014)	(.015)	(.014)	(.025)	(.015)	(.016)	(.013)	(.029)	(.016)	(.013)	(.019)	(.019)
Advertising Stock/Assets	-.051	.212	-1.05	-.370	.077	.096	-.903	-.422	-.928	-.286	-1.13	-.911
	(.529)	(.275)	(.673)	(.352)	(.542)	(.286)	(.682)	(.403)	(.585)	(.301)	(.889)	(.399)
Patents/R&D (MMs)	.031	.017	.025	.020	.032	.016	.023	.021	.026	.012	.027	.012
	(.011)	(.006)	(.021)	(.012)	(.011)	(.006)	(.019)	(.011)	(.010)	(.005)	(.020)	(.008)
Citations/Patent	.006	.003	.006	.002	.006	.003	.006	.002	.004	.003	.007	.003
	(.001)	(.000)	(.001)	(.001)	(.001)	(.000)	(.001)	(.001)	(.001)	(.000)	(.001)	(.000)
Generality	.103	.151	-.025	.109	.132	.125	-.092	-.009	.117	.187	-.066	.192
	(.104)	(.065)	(.166)	(.119)	(.105)	(.068)	(.157)	(.120)	(.119)	(.079)	(.203)	(.130)
Multisegment Firm Dummy = 1	-.185	-.121	-.059	-.017	-.069	-.066	-.004	-.024	-.148	-.124	-.027	-.039
	(.043)	(.027)	(.057)	(.042)	(.041)	(.028)	(.054)	(.043)	(.049)	(.029)	(.070)	(.048)
Technological Diversification = 1	.061	.021	-.119	-.100	.062	.044	-.117	-.078	.143	-.016	-.124	-.115
	(.042)	(.024)	(.042)	(.030)	(.042)	(.025)	(.042)	(.030)	(.046)	(.027)	(.051)	(.031)
No Advertising Dummy = 1	.125	.071	.168	.125	.140	.061	.147	.072	.159	.107	.239	.134
	(.042)	(.026)	(.088)	(.069)	(.042)	(.026)	(.042)	(.074)	(.048)	(.028)	(.113)	(.073)
Number of Obs.	9,969	8,384	9,969	8,384	9,969	8,472	9,969	8,472	9,969	6,842	9,969	6,842
R-squared	.063	.039	.054	.034	.057	.029	.005	.029	.181	.062	.215	.066
Sample	Median *q*	Median *q* Drop extreme *q*	Median *q*	Median *q* Drop extreme *q*	Median *q*	Median *q* Drop Extreme *q*	Median *q*	Median *q* Drop extreme *q*	Mean *q*	Mean *q* Drop extreme *q*	Mean *q*	Mean *q* Drop extreme *q*

The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years. Robust standard errors clustered by firm in parentheses. A full set of year dummies are included in each estimation. For Columns 1-4, the dependent variable is the log of the ratio of Tobin's q to imputed q. Imputed q is based on the median value of q for single-segment firms in each of the firm's segments, and then weighted by the firm's book value of assets in each segment. In Columns 5-8, the dependent variable is the log of the ratio of Tobin's q to the median q for the firm's primary SIC. In Columns 9-12, the dependent variable is the log of the ratio of Tobin's q to imputed q. Imputed q is based on the mean value of q for single-segment firms in each of the firm's segments, and then weighted by the firm's book value of assets in each segment. The primary industry or single-segment q values are based on the narrowest SIC group with at least 5 firms. Extreme q is defined as the log of excess q being greater than 1.386 or less than -1.386, implying excess value of greater than 400% or less than 25% of imputed q.

Table 9: Mean and Median Tobin's *q* by Technological Diversity, 1984-2002

	Number of Technology Categories					
	1	2	3-7	8-15	16+	Total
Single Segment	2.85 (1.29) {1,897}	2.85 (1.34) {1,534}	2.41 (1.23) {2,902}	1.81 (.997) {677}	1.40 (.893) {389}	**2.50** **(1.21)** **{7,399}**
Multi Segment	2.13 (.933) {329}	1.36 (.767) {314}	1.44 (.834) {445}	1.15 (.814) {468}	1.06 (.805) {621}	**1.37** **(.823)** **{2,570}**
	1	**2**	**3-7**	**8-15**	**16+**	**Total**
0-50th Percentile Patent stock	2.77 (1.17) (2.097}	2.68 (1.25) {1,556}	2.08 (1.14) {1,332}	--- --- {1}	--- --- {0}	**2.56** **(1.18)** **{4,986}**
50-80th Percentile Patent stock	2.13 (1.41) {124}	2.13 (1.17) {290}	2.14 (1.07) {2,156}	1.04 (.646) {415}	1.01 (.901) {7}	**1.99** **(1.01)** **{2,992}**
80-95th Percentile Patent stock	4.07 (4.22) {5}	--- --- {2}	3.04 (1.51) {251}	1.78 (1.08) {720}	1.02 (.797) {516}	**1.74** **(.995)** **{1,494}**
95th+ Percentile Patent stock	--- --- {0}	--- --- {0}	--- --- {0}	5.24 (2.92) {9}	1.37 (.870) {487}	**1.45** **(.881)** **{497}**
	1	**2**	**3-7**	**8-15**	**16+**	**Total**
0-10th Percentile Generality	2.15 (1.04) {446}	2.20 (1.24) {238}	1.73 (1.01) {231}	1.74 (1.57) {58}	1.74 (1.82) {16}	**2.04** **(1.13)** **{998}**
10-33rd Percentile Generality	2.77 (1.12) {469}	2.70 (1.14) {387}	1.91 (1.04) {883}	1.35 (.963) {325}	1.40 (.823) {254}	**2.09** **(1.02)** **{2,310}**
33rd-66th Percentile Generality	2.56 (1.00) {470}	2.67 (.998) {458}	2.09 (1.13) {1,238}	1.64 (.879) {497}	1.08 (.826) {646}	**1.97** **(.951)** **{3,309}**
66th-90th Percentile Generality	3.41 (1.44) {507}	2.50 (1.28) {471}	2.46 (1.22) {1,061}	1.53 (.820) {267}	1.31 (.842) {104}	**2.52** **(1.20)** **{2,410}**
90th+ Percentile Generality	2.72 (1.49) {339}	2.80 (1.64) {301}	2.65 (1.42) {350}	1.46 (1.16) {16}	--- --- {0}	**2.70** **(1.47)** **{1,006}**

	1	**2**	**3-7**	**8-15**	**16+**	**Total**
0-50th Percentile Cites per Patent	1.90 (.846) {1,002}	1.79 (.976) {821}	1.71 (.920) {1,860}	1.12 (.789) {638}	.974 (.798) {659}	**1.59** **(.864)** **{4,980}**
50-80th Percentile Cites per Patent	3.18 (1.32) {559}	2.78 (1.42) {506}	2.28 (1.23) {1,208}	1.98 (.986) {381}	1.50 (.908) {249}	**2.41** **(1.18)** **{2,987}**
80-95th Percentile Cites per Patent	3.28 (1.60) {430}	3.46 (1.53) {369}	3.01 (1.55) {553}	2.41 (1.44) {107}	2.46 (1.05) {35}	**3.14** **(1.55)** **{1,494}**
95th+ Percentile Cites per Patent	4.29 (2.16) {235}	4.22 (2.05) {152}	4.76 (2.49) {119}	--- --- {2}	--- --- {0}	**4.37** **(2.20)** **{508}**
All	**2.74** **(1.20)** **{2,226}**	**2.60** **(1.24)** **{1,848}**	**2.19** **(1.13)** **{3,740}**	**1.54** **(.910)** **{1,145}**	**1.19** **(.837)** **{1,010}**	2.21 (1.07) {9,969}

The first number in each cell is the mean q for each group, the second number in parentheses is the median q for the group, and the third number in braces is the number of observations in each group. Percentiles are reranked each year.

Table 10: Mean and Median Tobin's q by Generality

	Generality					
	0-10th Percentile	10-33rd Percentile	33rd-66th Percentile	66th-90th Percentile	90th+ Percentile	Total
Single Segment	2.21 (1.22) {802}	2.39 (1.12) {1,620}	2.26 (1.06) {2,258}	2.86 (1.39) {1,906}	2.82 (1.60) {848}	**2.50** **(1.21)** **{7,399}**
Multi-Segment	1.28 (.908) {187}	1.38 (.789) {690}	1.35 (.827) {1,051}	1.23 (.778) {504}	2.06 (.980) {158}	**1.37** **(.823)** **{2,570}**
	0-10th Percentile	**10-33rd Percentile**	**33rd-66th Percentile**	**66th-90th Percentile**	**90th+ Percentile**	**Total**
0-50th Percentile Patent stock	2.10 (1.05) {693}	2.53 (1.06) {927}	2.53 (1.04) {1,160}	2.78 (1.33) {1,386}	2.64 (1.47) {838}	**2.56** **(1.18)** **{4,986}**
50-80th Percentile Patent stock	1.87 (1.05) {225}	1.73 (1.01) {819}	1.79 (.911) {1,082}	2.35 (1.12) {724}	3.09 (1.46) {160}	**1.99** **(1.01)** **{2,992}**
80-95th Percentile Patent stock	1.93 (1.69) {62}	1.96 (1.05) {426}	1.64 (.938) {728}	1.62 (.880) {281}	1.34 (1.48) {8}	**1.74** **(.995)** **{1,484}**
95th+ Percentile Patent stock	1.75 (1.78) {9}	1.61 (.868) {138}	1.30 (.861) {339}	2.86 (1.27) {19}	--- --- {0}	**1.45** **(.881)** **{497}**
	0-10th Percentile	**10-33rd Percentile**	**33rd-66th Percentile**	**66th-90th Percentile**	**90th+ Percentile**	**Total**
0-50th Percentile Cites per Patent	1.80 (1.05) {609}	1.51 (.823) {1,304}	1.40 (.823) {1,777}	1.74 (.888) {965}	2.07 (1.05) {351}	**1.59** **(.864)** **{4,980}**
50-80th Percentile Cites per Patent	2.22 (1.20) {235}	2.21 (1.22) {652}	2.45 (1.04) {1,054}	2.62 (1.24) {785}	2.26 (1.53) {279}	**2.41** **(1.18)** **{2,987}**
80-95th Percentile Cites per Patent	2.75 (1.24) {114}	3.82 (1.72) {264}	3.04 (1.39) {399}	2.96 (1.54) {498}	3.09 (1.74) {226}	**3.14** **(1.55)** **{1,494}**
95th+ Percentile Cites per Patent	2.56 (2.01) {31}	4.41 (2.60) {90}	3.11 (1.64) {79}	5.27 (2.57) {162}	4.40 (1.91) {150}	**4.37** **(2.20)** **{508}**
	0-10th Percentile	**10-33rd Percentile**	**33rd-66th Percentile**	**66th-90th Percentile**	**90th+ Percentile**	**Total**
Total	**2.04** **(1.13)** **{989}**	**2.08** **(1.02)** **{2,310}**	**1.97** **(.951)** **{3,309}**	**2.51** **(1.20)** **{2,410}**	**2.70** **(1.46)** **{1,006}**	2.21 (1.07) {9,969}

The first number in each cell is the mean q for each group, the second number in parentheses is the median q for the group, and the third number in braces is the number of observations in each group. Percentiles are reranked each year.

Table 11: Patent Quality, Generality, and Diversity and Tobin's q, 1984-2002

	(1) OLS Ln(q)	(2) OLS Ln(q)	(3) FE Ln(q)	(4) OLS Segment Data	(5) OLS Segment Data	(6) FE Segment Data	(7) FE Segment Data	(8) OLS Segment Data	(9) OLS Segment Data	(10) FE Segment Data	(11) FE Segment Data
R&D/Assets	.117	.115	.087	.113	.013	.087	-.010	.107	.067	.071	.075
	(.013)	(.014)	(.013)	(.013)	(.016)	(.014)	(.025)	(.015)	(.013)	(.019)	(.019)
Advertising Stock/Assets	.047	-.170	-.996	-.072	.174	-1.14	-.428	-.907	-.321	-1.19	-.986
	(.569)	(.585)	(.755)	(.529)	(.273)	(.675)	(.350)	(.580)	(.304)	(.893)	(.394)
Patents/R&D	.032	.037	.028	.031	.018	.027	.022	.025	.013	.030	.013
	(.012)	(.014)	(.021)	(.012)	(.007)	(.022)	(.013)	(.022)	(.022)	(.021)	(.009)
Multisegment Firm (D=1)	-.199	-.141	.006	-.187	-.111	-.050	-.008	-.181	-.115	-.017	-.029
	(.043)	(.048)	(.053)	(.043)	(.028)	(.057)	(.042)	(.050)	(.030)	(.069)	(.048)
No Advertising (D=1)	.134	.176	.183	.132	.074	.166	.116	.171	.107	.239	.130
	(.042)	(.043)	(.094)	(.042)	(.026)	(.086)	(.067)	(.047)	(.028)	(.111)	(.073)
2 Technology Categories (D=1)	.014	.013	-.086	.028	.032	-.081	-.058	.031	.017	-.077	-.072
	(.049)	(.049)	(.045)	(.048)	(.029)	(.043)	(.031)	(.054)	(.031)	(.052)	(.032)
3-7 Technology Categories (D=1)	.021	.038	-.202	.065	.036	-.173	-.139	.145	-.010	-.200	-.173
	(.048)	(.047)	(.052)	(.046)	(.031)	(.052)	(.035)	(.052)	(.031)	(.062)	(.036)
8-15 Technology Categories (D=1)	.029	.047	-.333	.106	-.001	-.284	-.269	.235	-.056	-.293	-.262
	(.066)	(.062)	(.076)	(.062)	(.042)	(.077)	(.056)	(.072)	(.046)	(.093)	(.060)
16+ Technology Categories (D=1)	.111	.231	-.261	.240	.090	-.297	-.247	.392	.014	-.145	-.235
	(.066)	(.073)	(.117)	(.066)	(.044)	(.118)	(.086)	(.076)	(.048)	(.137)	(.081)
Generality in 0-10th percentile (D=1)	.120	.066	.080	.068	.029	.040	.024	.049	-.029	.092	-.064
	(.063)	(.058)	(.067)	(.059)	(.038)	(.073)	(.053)	(.068)	(.050)	(.091)	(.057)
Generality in 10th-33rd percentile (D=1)	.071	.047	.078	.058	.004	.083	.024	.044	.004	.080	.015
	(.041)	(.042)	(.036)	(.041)	(.026)	(.039)	(.028)	(.047)	(.029)	(.047)	(.030)
Generality in 66th-90th percentile (D=1)	.090	.098	.042	.079	.068	.052	.048	.059	.046	.077	.029
	(.043)	(.042)	(.044)	(.041)	(.026)	(.044)	(.030)	(.046)	(.027)	(.050)	(.030)
Generality in 90th+ percentile (D=1)	.176	.158	.086	.155	.101	.117	.087	.115	.065	.143	.041
	(.061)	(.060)	(.073)	(.056)	(.036)	(.074)	(.050)	(.064)	(.038)	(.086)	(.048)
Cites per patent in 50th-80th Percentile (D= 1)	.308	.238	.082	.203	.091	.066	.016	.184	.060	.097	.018
	(.039)	(.040)	(.039)	(.037)	(.024)	(.040)	(.029)	(.043)	(.024)	(.049)	(.029)
Cites per patent in 80th-95th Percentile (D= 1)	.521	.408	.239	.341	.182	.200	.108	.278	.153	.274	.112
	(.054)	(.055)	(.064)	(.051)	(.030)	(.065)	(.044)	(.057)	(.034)	(.075)	(.045)
Cites per patent in 95th+ Percentile (D= 1)	.791	.625	.412	.566	.284	.370	.140	.357	.287	.349	.220
	(.082)	(.086)	(.097)	(.079)	(.050)	(.095)	(.073)	(.087)	(.056)	(.112)	(.076)
Number of Observations	9,969	9,969	9,969	9,969	8,384	9,969	8,384	9,969	6,842	9,969	6,842
R-squared	.191	.249	.137	.068	.042	.056	.004	.186	.062	.215	.215
Controls	Year	Year 4-Digit SIC	Year	Year	Year	Year	Year	Year	Year	Year	Year
Sample				Median q	Median q Drop Extreme q	Median q	Median q Drop Extreme q	Mean q	Mean q Drop Extreme q	Mean q	Mean q Drop Extreme q

The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years. Robust standard errors clustered by firm in parentheses. In Columns 1-3, the dependent variable is the log of Tobin's q. For Columns 4-11, the dependent variable is the log of the ratio of Tobin's q to imputed q. Imputed q is based on the value of q for single-segment firms in each of the firm's segments, and then weighted by the firm's book value of assets in each segment. In Columns 4-7, imputed q is based on median q, in Columns 8-11, it is based on mean q. The single-segment q values are based on the narrowest SIC group with at least 5 firms. Extreme q is defined as the log of excess q being greater than 1.386 or less than -1.386, implying excess value of greater than 400% or less than 25% of imputed q.

Table 12: Loss of Technological Leadership and Tobin's q, 1984-2002

	(1) OLS Ln(q)	(2) OLS Ln(q)	(3) FE Ln(q)	(4) OLS Seg. Data	(5) OLS Seg. Data	(6) FE Seg. Data	(7) FE Seg. Data	(8) OLS Seg. Data	(9) OLS Seg. Data	(10) FE Seg. Data	(11) FE Seg. Data
R&D/Assets	.120	.115	.089	.113	.013	.088	-.007	.107	.067	.073	.075
	(.014)	(.014)	(.013)	(.014)	(.016)	(.014)	(.025)	(.016)	(.013)	(.019)	(.019)
Advertising Stock/Assets	.022	-.140	-.944	-.092	.172	-1.10	-.401	-.952	-.303	-1.16	-.943
	(.571)	(.588)	(.747)	(.527)	(.270)	(.668)	(.350)	(.584)	(.299)	(.885)	(.394)
Patents/R&D (MMs)	.030	.037	.025	.031	.018	.024	.020	.026	.012	.027	.011
	(.012)	(.013)	(.019)	(.011)	(.006)	(.021)	(.011)	(.011)	(.005)	(.019)	(.008)
Cites/Patent	.008	.006	.006	.006	.003	.006	.002	.004	.003	.007	.003
	(.001)	(.001)	(.001)	(.001)	(.000)	(.001)	(.001)	(.001)	(.000)	(.001)	(.001)
Multisegment Firm Dummy = 1	-.226	-.134	-.006	-.176	-.113	-.056	-.014	-.145	-.120	-.028	-.035
	(.042)	(.050)	(.054)	(.042)	(.028)	(.057)	(.042)	(.050)	(.029)	(.070)	(.049)
Multiple Tech Categories	.012	.034	-.134	.061	.025	-.119	-.100	.147	-.008	-.118	-.114
	(.043)	(.041)	(.042)	(.041)	(.025)	(.041)	(.029)	(.046)	(.027)	(.051)	(.031)
No Advertising Dummy = 1	.126	.166	.183	.123	.069	.166	.124	.157	.105	.238	.132
	(.043)	(.044)	(.095)	(.042)	(.026)	(.088)	(.068)	(.047)	(.028)	(.112)	(.072)
Loss of Leadership	-.321	-.287	-.204	-.314	-.157	-.182	-.131	-.234	-.099	-.132	-.137
	(.131)	(.131)	(.096)	(.125)	(.088)	(.097)	(.081)	(.148)	(.092)	(.108)	(.080)
Loss of Leadership * Multi-tech firm	.147	.105	.058	.151	.072	.050	.059	.012	.039	-053	.027
	(.129)	(.126)	(.095)	(.121)	(.079)	(.097)	(.074)	(.142)	(.088)	(.107)	(.074)
Loss of Leadership * Multisegment	-.072	-.081	-.076	-.175	-.106	-.148	-.092	-.138	-.045	-.061	-.059
	(.119)	(.119)	(.091)	(.117)	(.085)	(.091)	(.068)	(.151)	(.087)	(.106)	(.078)
Loss of leadership * High Generality	.250	.240	.162	.283	.143	.203	.148	.199	.139	.126	.142
	(.116)	(.116)	(.088)	(.111)	(.078)	(.086)	(.070)	(.139)	(.084)	(.105)	(.073)
Loss of Leadership * Low Generality	.082	.066	.003	.070	.075	-.011	.023	-.018	.047	-.055	.077
	(.128)	(.126)	(.098)	(.123)	(.081)	(.098)	(.070)	(.136)	(.088)	(.110)	(.077)
Dummy: Generality High	.091	.086	.044	.061	.067	.054	.058	.019	.063	.082	.061
	(.040)	(.041)	(.045)	(.039)	(.025)	(.044)	(.030)	(.044)	(.026)	(.051)	(.030)
Dummy: Generality Low	.061	.024	.078	.030	-.001	.076	.026	.005	-.002	.082	.002
	(.039)	(.039)	(.037)	(.38)	(.024)	(.039)	(.028)	(.045)	(.027)	(.048)	(.029)
Number of Observations	9,969	9,969	9,969	9,969	8,384	9,969	8,384	9,969	6,842	9,969	6,842
R-squared	.186	.246	.138	.065	.041	.056	.004	.182	.063	.217	.215
Controls	Year	Year 4-Digit SIC	Year	Year	Year	Year	Year	Year	Year	Year	Year
Sample				Median q	Median q Drop Extreme q	Median q	Median q Drop Extreme q	Mean q	Mean q Drop Extreme q	Mean q	Mean q Drop Extreme q

The sample consists of firms with at least one high-tech business segment, at least $1 million of R&D, a patent stock of at least 1, and at least one patent application in the previous five years. Robust standard errors clustered by firm in parentheses. In Columns 1-3, the dependent variable is the log of Tobin's q. For Columns 4-11, the dependent variable is the log of the ratio of Tobin's q to imputed q. Imputed q is based on the value of q for single-segment firms in each of the firm's segments, and then weighted by the firm's book value of assets in each segment. In Columns 4-7, imputed q is based on median q, in Columns 8-11, it is based on mean q. The single-segment q values are based on the narrowest SIC group with at least 5 firms. Extreme q is defined as the log of excess q being greater than 1.386 or less than -1.386, implying excess value of greater than 400% or less than 25% of imputed q.

References

Aizcorbe, A. M., Moylan, C. E., and Robbins, C. A. 2009. "Toward Better Measurement of Innovation and Intangibles," *Survey of Current Business* (89:1), January, pp. 10-23.

Barth, M.E., Clement, M.B., Foster, G., and Kaznik, R. 1998. "Brand Values and Capital Market Valuation," *Review of Accounting Studies* (3:1-2), March, pp. 41-68.

Berger, P.G, and Hann, R. 2003. "The Impact of SFAS No. 131 on Information and Monitoring," *Journal of Accounting Research* (41:2), May, pp. 163-223.

Berger, P.G, and Ofek E. 1995. "Diversification's Effect on Firm Value," *Journal of Financial Economics* (37:1), January, pp. 39-65.

Bresnahan, T.F., and Trajtenberg, M. 1995. "General Purpose Technologies: Engines of Growth?" *Journal of Econometrics* (65:1), January, pp. 83-108.

Brynjolfsson, E., Hitt, L. M., and Yang, S. 2002. "Intangible Assets: Computers and Organizational Capital," *Brookings Papers on Economic Activity* (2002:1), pp. 137-181.

Campa, J.M., and Kedia, S. 2002. "Explaining the Diversification Discount," *Journal of Finance* (57:4), August, pp. 1731-1762.

Chung, K.H., and Pruitt, S.W. 1994. "A Simple Approximation of Tobin's *q*," *Financial Management* (23:3), Autumn, pp. 70-74.

Cockburn, I., and Griliches, Z. 1988. "Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents," *American Economic Review* (78:2), May, pp. 419-23.

Corrado, C., Hulten, C., and Sichel, D. 2005. "Measuring Capital and Technology: An Expanded Framework," in *Measuring Capital in the New Economy*, C. Corrado, J. Haltiwanger, and D. Sichel (eds.), Chicago: University of Chicago Press, pp. 11-46.

Corrado, C., Hulten, C., and Sichel, D. 2009. "Intangible Capital and Economic Growth," *Review of Income and Wealth* (55:3), September, pp. 661-685.

Griliches, Z. 1981. "Market Value, R&D and Patents," *Economics Letters* (7:2), pp. 183-187.

Griliches, Z., and Hausman, J.A. 1986. "Errors in Variables in Panel Data," *Journal of Econometrics* (31:1), February, pp. 93-118.

Hall, B.H. 1993. "The Stock Market's Valuation of R&D Investment during the 1980s," *American Economic Review* (83:2), May, pp. 259–64.

Hall, B.H., Jaffe, A.B., and Trajtenberg, M. 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," NBER Working Paper 8498, October. Available at http://www.nber.org/papers/w8498.

Hall, B.H., Jaffe, A., and Trajtenberg, M. 2005. "Market Value and Patent Citations," *The Rand Journal of Economics* (36:1), Spring, pp. 16-38.

Hall, R.E. 2000. "E-Capital: The Link between the Stock Market and the Labor Market in the 1990s," *Brookings Papers on Economic Activity* (2000:2), pp. 73-118.

Hall, R.E. 2001. "The Stock Market and Capital Accumulation," *The American Economic Review* (91:5), December, pp. 1185-1202.

Hayashi, F. 1982. "Tobin's Marginal *q* and Average *q*: A Neo-classical Interpretation," *Econometrica*, (50:1), January, pp. 213-224.

Hirschey, M., and Weygand, J.J. 1985. "Amortization Policy for Advertising and Research and Development Expenditures," *Journal of Accounting Research* (23:1), Spring, pp. 326-335.

Lang, L., and Stulz, R. 1994. "Tobin's *q*, Corporate Diversification, and Firm Performance," *Journal of Political Economy* (102:x), month, pp. 1248-1280.

Lindenberg, E.B., and Ross, S.A. 1981. "Tobin's *q* ratio and Industrial Organization," *Journal of Business* (54:1), January, pp. 1-32.

Maksimovic, V., and Phillips, G. 2007. "Conglomerate Firms and Internal Capital Markets," in *Handbook of Corporate Finance, Volume 1*, B.E. Eckbo (ed), Amsterdam: Elsevier, pp. 423-479.

McGahan, A.M., and Silverman, B.S. 2006. "Profiting from Technological Innovation by Others: The Effect of Competitor Patenting on Firm Value," *Research Policy* (35:8), October, pp. 1222-1242.

Morck, R., and Yeung, B. 2003. "Why Firms Diversify: Internalization vs. Agency Behaviour," in *Intangible Assets: Values, Measures, and Risks,* J. Hand and B. Lev (eds.), New York: Oxford University Press, pp. 269-302.

Nakamura, L. 2001. "What is the U.S. Gross Investment in Intangibles? (At least) One Trillion Dollars a Year!" *Working Paper No. 01-15, Federal Reserve Bank of Philadelphia.* October.

Roberts, P.W., and Dowling, G.R. 2002. "Corporate Reputation and Sustained Superior Financial Performance," *Strategic Management Journal* (23:12), December, pp. 1077-1093.

Saunders, A. 2011. "Valuing IT-Related Intangible Capital," Working Paper, MIT.

Teece, D.J., Pisano, G., and Shuen, A. 1997. "Dynamic Capabilities and Strategic Management," *Strategic Management Journal* (18:7), August, pp. 509-533.

Tobin, J. 1969. "A General Equilibrium Approach to Monetary Theory," *Journal of Money, Credit and Banking* (1:1), February, pp. 15–29.

Trajtenberg, M., Jaffe, A., and Henderson, R. 1997. "University versus Corporate Patents: A Window on the Basicness of Invention," *Economics of Innovation and New Technology* (5:1), May, pp. 19-50.

Villalonga, B. 2004a. "Diversification Discount or Premium? New Evidence from the Business Information Tracking Series," *Journal of Finance* (59:2), April, pp. 479-506.

Villalonga, B. 2004b. "Does Diversification Cause the Diversification Discount?" *Financial Management* (33:2), Summer, pp. 5-27.

Villalonga, B. 2004c. "Intangible resources, Tobin's q, and sustainability of performance differences," *Journal of Economic Behavior and Organization* (54:2), June, pp. 205-230.

Wernerfelt, B., and Montgomery, C.A. 1988. "Tobin's *q* and the Importance of Focus in Firm Performance," *American Economic Review* (78:1), March, pp. 246-50.

Zhao, R. 2002. "Relative Value Relevance of R&D Reporting: An International Comparison," *Journal of International Financial Management and Accounting* (13:2), Summer, pp. 153-174.