Investigating the Risk-Return Relationship of Information Technology Investment: Firm-Level Empirical Analysis

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This paper develops empirical proxy measures of IT risk, and incorporates them into the usual empirical models for analyzing IT returns: production function and market value specifications. The results suggest that IT capital investment makes a substantially larger contribution to overall firm risk than non-IT capital investments. Further, firms with higher IT risk have a higher marginal product of IT relative to firms with low IT risk. In the market value specification, the impact of IT risk is positive and significant, and inclusion of the IT risk term substantially reduces the coefficient on IT capital. We estimate that about 30% of the gross return on IT investment corresponds to the risk premium associated with IT risk. Taken together, our results show that IT risk provides part of the explanation for the unusually high valuations of IT capital investment in recent research.

Key words: IT capital; productivity paradox; IT returns; IT risk; IT investment; IT value; real options

1. Introduction

There is widespread recognition that investments in IT are inherently risky due to uncertainty about their economic impact, technological complexity, rapid obsolescence, implementation challenges, and so forth.[1] The interplay between risk and return plays a central role in the evaluation of investments in the financial economics literature, and is therefore a key element in models for asset and options pricing (Brealey and Myers 2002). In contrast, consideration of risk is virtually absent in the growing literature on the returns on IT investment, even though the risks are widely recognized.

Motivated by the evidence of unusually high IT valuations in recent empirical analyses (see Dedrick et al. 2003 for a recent survey), our aim is to develop an understanding of the risk-return profile of IT investment by incorporating IT risk into the primary empirical approaches for characterizing IT returns:

production function analysis and market value analyses. We examine the following research questions: How risky are IT investments relative to other types of capital investment? What is the impact of IT risk on the required rate of return on IT investment, and on the productivity and market value of firms?

At the outset, it is useful to explain what we mean by "return" and "risk" in the context of this research. We use the term *return on IT investment* (or simply, IT returns) to generically refer to the payoffs from IT investments, accruing from the incremental cash flows resulting from these investments. We define *IT risk* as the ex ante uncertainty associated with IT returns. As such, IT risk is one component of the overall riskiness of a firm's cash flows, and can be a significant component for IT-intensive firms. The source of IT risk is the observation that IT investments can result in a range of positive or negative incremental cash flows, but predicting the outcome at the time of the investment is difficult. Thus, we define IT risk as the variability of returns on IT investment, which is increased by *unexpected* positive or negative outcomes.

The academic literature has not focused on the risk-return relationship of IT investment. There is considerable prior work on both IT returns (Brynjolfsson and Hitt 1996, Dewan and Min 1997, Bharadwaj et al. 1999, Brynjolfsson et al. 2002), and on aspects of IT risk at the project or systems implementation level (Alter and Ginzberg 1978, Boehm 1989, Keil et al. 1998, Lyytinen et al. 1998, Benaroch 2002). Hunter et al. (2003), in a concurrent research effort, examine the impact of IT investments on the volatility of earnings; their focus is on the determinants of IT risk at the industry and firm level, and they do not study the risk-return relationship.

Our analysis draws from options pricing theories of investment under uncertainty (see Schwartz and Trigeorgis 2001 for a survey). A firm with an investment opportunity holds a *real* option in that it has the right, but not the obligation, to make the investment at a time of its choosing, in return for a stream of incremental cash flows. In the presence of uncertainty, the option to wait has value (the option value) because of the ability to postpone the investment until some of the uncertainty has been resolved. When a

[1] For example, a survey by the Standish Group of over 8,000 IT projects found that 23% of projects failed outright, while an additional 49% were completed late or over-budget, or with fewer features than promised (BusinessWeek 2001). ERP systems reportedly have even higher failure rates (Hitt et al. 2002).

firm makes an irreversible investment, it has effectively exercised the option by giving up the possibility of waiting. Thus, the lost option value is an opportunity cost of making the investment, which correspondingly raises the hurdle rate of return. Indeed, recent studies have shown that managers often set hurdle rates that are three to four times the level predicted by systematic risk alone (Dixit and Pindyck 1995). To the extent that IT investment opportunities have the characteristics of real options, which we will argue below they do, the opportunity cost of exercising these options increases in IT risk and hence can be a significant contributor to the risk premium associated with investments in IT capital.

Our results show that IT investments are substantially riskier than non-IT capital investments, as measured by their relative contributions to the overall riskiness of the firm (proxied by stock-return volatility and earnings volatility). We develop a proxy measure for IT risk, and use it to analyze the risk-return relationship of IT investment. In the production function analysis, we find that firms with high IT risk have substantially higher IT output elasticity and IT marginal product relative to firms with low IT risk. In the market value analysis, we find the IT risk term to be positive and significant, and its addition reduces the magnitude of the coefficient on IT capital, suggesting that IT risk is a significant contributor to the required return on IT investment. A variety of robustness checks demonstrate that the qualitative nature of these results is not sensitive to alternative specifications and estimation methods.

Our paper is structured as follows. The next section provides the theoretical underpinnings of our analysis and develops our empirical predictions. In Section 3, we describe our research design and data. Results are in Section 4, and Section 5 concludes. There is an Online Appendix that provides additional tables and discussion.

2. Theoretical Background

2.1. IT Investments Literature

The weight of empirical evidence in the growing IT investments literature has shifted from the productivity paradox to the *new* productivity paradox (Anderson et al. 2003), wherein what is puzzling is no longer the lack of evidence of measurable IT returns, but rather, the abnormally high estimates of the same. Using the production function approach, Brynjolfsson and Hitt (1996) reported that the average marginal product of computer capital was 81% for their sample of firms, as compared to 6.26% for non-computer capital. Similar findings of excess returns were also reported by Lichtenberg (1995) and Dewan and Min (1997). Using a market value specification, Brynjolfsson et al. (2002) estimate IT valuation multiples in the range of 10-15; that is, an increase of $1 in IT capital stock is associated with an increase of $10-15 in the market valuation of firms. Focusing on the more recent time frame of 1999 to 2002, Anderson et al. (2003) analyze public disclosures of Y2K related spending, a significant portion of which went towards the implementation of ERP systems, and they report IT valuation multiples ranging from 26 to 62.

One explanation for the excess returns puzzle is that there is *hidden IT capital*, in that, there are several dollars of unmeasured IT capital for every measured dollar of IT capital, such as investments in software, outsourced applications and services, and decentralized investments that are difficult to track (see, e.g., Brynjolfsson and Hitt 1995). However, measurement error is unlikely to be large enough to fully account for the excess IT returns. Brynjolfsson et al. (2002) attribute the excess IT returns to complementary investments in organization restructuring and reengineering of business processes, which they refer to as investments in *organizational capital*. In the same vein, Anderson et al. (2003) note that investments in IT (which in their case is ERP systems) create *intangible asset value* by mobilizing other complementary investments in organizational assets, resulting in deeper knowledge about customers, tighter coordination of supply chains, etc.

The focus of this research is on another factor potentially contributing to high measured returns on IT investment — *IT risk*. That is, if IT investments are riskier than other types of investments, then the risk premium associated with these investments would contribute to the high measured gross returns. It is important to point out that the above explanations for the new productivity paradox are not mutually exclusive — they are "complementary" not "competing" explanations.

2.2. IT Investments as Real Options

The information systems literature has an established tradition of analyzing IT investments from an options theory perspective (e.g., Benaroch and Kauffman 1999, 2000, Taudes et al. 2000, Benaroch 2002, Schwartz and Zozaya-Gorostiza 2003, Fichman 2004). This stream of IS research, however, has focused on the *creation* of new call options in the form of managerial flexibility in specific IT projects, whereas this paper deals with the *exercise* of call options as firms make IT capital investments.[2] The closest theoretical antecedents to this work are the options pricing models of irreversible investment under uncertainty developed by McDonald and Siegel (1986) and Dixit and Pindyck (1994), and adapted to certain types of IT investments by Schwartz and Zozaya-Gorostiza (2003). Specifically, these models are built around the valuation of the "option to defer" the timing of capital investments satisfying the IUT properties of *irreversibility*, *uncertainty* (about costs and benefits) and *timing* flexibility (Dixit and Pindyck 1994). In what follows, we make the case that general IT capital investments also satisfy these properties, building on the arguments of Fichman (2004).

Hardware investments are effectively irreversible since declining hardware cost trends (roughly 20% per year or greater) imply that the resale price of computer-related equipment is typically substantially lower than the purchase price. Software investments are also irreversible: in-house development costs and/or licensing fees are typically expensed immediately and therefore cannot be recovered. With respect to the uncertainty property, Fichman's (2004) arguments regarding the role of interpretive flexibility and knowledge barriers also apply to the case of IT capital investments in general. Finally, the time lags in the adoption of IT innovations, such as ERP systems and electronic commerce, suggest flexibility in the timing of IT investment to wait until the resolution of uncertainty about costs and benefits.[3] Timing flexibility is also reflected in the aggregate patterns of IT investment, which have been shown to be sensitive

[2] In general, capital investment can be viewed both as the exercise of a *call* option to expand capital stock and/or the simultaneous purchase of a *put* option to reverse the investments in the future. In the case of IT investments, however, the underlying cost trends are such that expandability strongly dominates reversibility of investment, resulting in the put option generally being "out of the money."

[3] A case in point is the adoption of ERP software, which was commercially introduced in the mid-eighties, but the push to implement such systems did not happen until the Y2K problem was close at hand (Anderson et al. 2003) and when uncertainty about the return on investment reduced quite dramatically.

to the business cycle (Gurbaxani and Mendelson 1992), not unlike durable goods in general. Further, Dewan et al. (1998) find empirical evidence indicating that that IT spending is positively associated with access to free cash flow, again suggesting that firms are able to synchronize IT investment with availability of discretionary financial resources.

We now summarize what options pricing theory has to say about the opportunity cost of exercising the option to wait before making an irreversible investment. Please see Section EC.1 in the Online Appendix for a more detailed account.

2.3. Lost Option Value of Irreversible Investment

Dixit and Pindyck (1994, Chapter 5) provide a detailed contingent claims analysis of the timing of an irreversible project under uncertainty. Specifically, they analyze a project calling for a fixed investment cost I and a random value V governed by a Brownian motion process, and show that the optimal ratio of value to cost (or the "marginal q") at the time of investment can be expressed as follows:

$$q^* = V^* / I = 1 + \psi(\sigma), \tag{1}$$

where $\psi(\sigma)$ is increasing in the value uncertainty parameter σ. That is, the threshold $q^* > 1$. Contrary to the simple NPV rule that sets $q^* = 1$, the options pricing investment rule calls for leaving the marginal q greater than unity in equilibrium, with the difference $q^* - 1 = \psi(\sigma)$ representing the "wedge" between the NPV and optimal investment rules, which is increasing in the uncertainty parameter σ. Qualitatively, the impact of investment risk is to raise the required or hurdle rate of return, reflecting the opportunity cost due to the lost option value of investment. This key insight from the options pricing theory of irreversible investment provides the essential link between risk and return in both the production function and market value specifications, and is the theoretical basis for the empirical models described in the following section.

3. Empirical Models and Data

3.1. Proxy Measures for IT Risk

Recent research in accounting and finance suggests two alternative measures for overall firm risk: (i) standard deviation of one-year daily stock returns following the investment (Carter et al. 1998), denoted by *SD(Returns)*, and (ii) standard deviation of realized annual earnings over 5 years following the investment (Kothari et al. 2002), denoted by *SD(Earnings)*. We consider both measures in parallel throughout our empirical analysis to ensure that the results are robust to the choice of market versus accounting measures of overall firm risk. We denote overall firm risk by σ, and the contributions of IT capital and non-IT capital to overall firm risk, by σ_{IT} and σ_K, respectively.

Our approach for estimating σ_{IT} and σ_K is analogous to the analysis of the contributions of R&D and non-R&D investments to overall firm risk by Kothari et al. (2002). Essentially, the approach is to regress a measure of overall firm risk on IT capital and non-IT capital stocks along with other controls as the independent variables. Specifically, for average aggregate values of measures of σ_{IT} and σ_K we estimate the following pooled regression model:

$$\begin{aligned}\sigma_{lt} &= \sigma_{IT} IT\_asset_{lt} + \sigma_K K\_asset_{lt} + \gamma_1 Size_{lt} + \gamma_2 Leverage_{lt} + \gamma_3 RD_{lt} + \gamma_4 Ad_{lt} \\ &+ \gamma_5 IndReg_l + \gamma_6 IndCap_l + \gamma_7 IndQ_l + \gamma_8 IndConc_l + \sum_{t=1987}^{1994} \gamma_t Year_t + \varepsilon_{lt},\end{aligned} \tag{2}$$

where for firm *l* in year *t*: σ_{lt} denotes firm risk, measured either by stock-returns variability or by earnings variability; *IT_asset* = IT capital stock, scaled by total assets; *K_asset* = non-IT capital stock, scaled by total assets; *Size* = firm size, proxied by the natural logarithm of market value of equity at fiscal year end (in millions of dollars); *Leverage* = long-term debt divided by total assets; *RD* = R&D intensity, computed as the ratio of annual R&D expenditure to annual sales; *Ad* = advertising intensity, computed as the ratio of annual advertising expenditure to annual sales. The firm-level variables for size, leverage, R&D and advertising intensities are included to control for other firm-specific drivers of overall firm risk, as in Kothari et al. (2002).

In addition, in order to control for differences in industry characteristics, following Bharadwaj et al. (1999), we have included four industry structure variables defined at the two-digit SIC level: an indicator variable for whether or not this is a regulated industry, *IndReg*; Industry capital intensity, *IndCap*; Industry q ratio, *IndQ*; and Industry four-firm concentration ratio, *IndConc*. As an additional robustness check, we also consider alternative industry controls based simply on industry dummy variables at the one- and two-digit SIC levels, respectively.[4] As will be shown in section 4.1, our results are not sensitive to the choice of alternative industry controls.

The estimated coefficients σ_{IT} reflects the *average* contribution of IT capital to overall firm risk. Ideally, we require an estimate of IT risk at the level of individual firms, but the obvious bottleneck is the lack of sufficient data at the firm level. The next best is to identify the effects of IT risk at a higher level of aggregation, such as at the level of suitably defined industry segments, which is the approach we take. To form industry segments, we need to strike a balance between our goal of generating IT risk estimates with wide cross-sectional variations in value and the necessity of having an adequate number of observations within each industry group to allow reliable estimation of industry-specific coefficients. Suppose there are J industry segments, indexed by $j = 1, \ldots, J$. To estimate industry-specific IT risk measures, we modify the regression model (2) by allowing the coefficient of *IT_asset* to vary across the J industry segments. Specifically, we run the following risk regression model:

$$\begin{aligned}\sigma_{lt} = \sum_{j=1}^{J} \sigma_{IT,j}\, IT\_asset_{lt} \times IND_{lj} + \sigma_K\, K\_asset_{lt} + \gamma_1\, Size_{lt} + \gamma_2\, Leverage_{lt} + \gamma_3\, RD_{lt} + \gamma_4\, Ad_{lt} \\ + \gamma_5\, IndReg_l + \gamma_6\, IndCap_l + \gamma_7\, IndQ_l + \gamma_8\, IndConc_l + \sum_{t=1987}^{1994} \gamma_t\, Year_t + \varepsilon_{lt},\end{aligned} \tag{3}$$

where for firm l in year t, $\text{IND}_{lj} = 1$ if firm l is in industry j, and 0 otherwise. All other variables are defined as in regression (2). Note that for each industry $j = 1, \ldots, J$, the coefficient $\sigma_{IT,j}$ reflects the proportion of firm risk attributable to IT capital investment, on average, for that industry. The coefficients $\{\sigma_{IT,j}, j = 1, \ldots, J\}$ collectively constitute our proxy measure for IT risk. Note that while we expect most of these coefficients to be positive (i.e., IT investments are associated with higher firm risk), our theoreti-

[4] We thank an anonymous reviewer for stressing the importance of controlling for industry heterogeneity, which motivated us to consider the more rigorous industry controls described here.

cal framework does not rule out negative coefficients (i.e., IT investments are associated with lower firm risk), consistent with the analysis of Hunter et al. (2003).[5]

3.2. IT Risk-Return Specifications

We now describe how we incorporate IT risk into the production function and market value specifications.

3.2.1. Production Function

Consistent with prior studies (e.g., Dewan and Min 1997), we adopt a standard Cobb-Douglas production function, specified in a log-linear form as follows:

$$\begin{aligned} \ln VA_{lt} &= \beta_0 + \beta_1 \ln IT_{lt} + \beta_2 \ln K_{lt} + \beta_3 \ln L_{lt} \\ &+ \beta_4 IndReg_l + \beta_5 IndCap_l + \beta_6 IndQ_l + \beta_7 IndConc_l + \sum_{t=1987}^{1994} \beta_t Year_t + \varepsilon_{lt}, \end{aligned} \tag{4}$$

where for firm l in year t: VA_{lt} = value added (equal to sales less cost of materials); IT_{lt} = IT capital stock; K_{lt} = non-IT capital stock; L_{lt} = labor cost; and the industry and year controls are as in regressions (2)-(3). The input and output variables in the production function are denominated in millions of constant dollars, consistent with the prior IT production function literature (see, e.g., Brynjolfsson and Hitt 1996 and Dewan and Min 1997). The slope coefficients, β_1, β_2 and β_3 represent the output elasticities with respect to IT capital, non-IT capital, and labor, respectively. The marginal product of IT capital (i.e., the increase in value added associated with a one dollar increase in IT capital stock) is given by $\beta_1 \cdot VA_{lt} / IT_{lt}$, and is the proxy measure of IT return obtained from the production function estimation.

Next, we discuss how we incorporate IT risk into the production function framework. First, note that IT risk is not a factor of production but a source of heterogeneity among firms. Accordingly, we cannot introduce IT risk directly into the regression as another explanatory variable. Rather, we use the IT risk

[5] We do not incorporate disaggregated estimates of non-IT capital risk in our analysis, for two reasons. First, the contribution of non-IT capital to overall firm risk is arguably negligible (see Table 3). Second, when we do include non-IT capital risk estimates in the market value regressions, our findings are virtually unchanged as compared to the case when non-IT capital risk is left out.

variable to distinguish between firms in high and low IT risk industries, and conduct a comparative sample-split analysis. Following our theoretical discussion in Section 2.3, we expect that firms in High IT Risk industries will be characterized by a higher marginal product of IT investment relative to Low IT Risk firms, all else being equal.

3.2.2. Market Value Specification

We start by describing the results of Brynjolfsson et al. (2002), who conducted an analysis of IT returns in a market value specification, using the following regression model:

$$\begin{aligned} TV_{lt} &= \beta_0 + \beta_1 IT_{lt} + \beta_2 K_{lt} + \beta_3 OA_{lt} + \beta_4 RD_{lt} + \beta_5 Ad_{lt} \\ &\quad + \beta_6 IndReg_l + \beta_7 IndCap_l + \beta_8 IndQ_l + \beta_9 IndConc_l + \sum_{t=1987}^{1994} \beta_t Year_t + \varepsilon_{lt}, \end{aligned} \tag{5}$$

where for firm *l* in year *t*: TV_{lt} = total firm value (sum of the market value of common stock at the fiscal year end, liquidating value of preferred stock, and the book value of total debt); IT_{lt} = IT capital stock; K_{lt} = non-IT capital stock, the difference between the net stock of Property, Plant, and Equipment (PPE) and IT capital stock; OA_{lt} = other assets (difference between total assets and net stock of PPE); RD_{lt} (R&D intensity), Ad_{lt} (advertising intensity), and the industry and year controls are as in regression (2).

Brynjolfsson et al. (2002) estimate the coefficient of IT, β_1, to be 14.59. When they add a proxy measure of organizational capital to the market value regression, it drives down the IT coefficient to the range of 5 to 11, depending on the regression specification used. It is worth noting that the coefficient of IT capital is still substantially greater than unity, even after controlling for organizational capital.

Options pricing theory predicts that $\beta_1 > 1$, due to the opportunity cost of the lost option value. Additionally, marginal *q* would be further inflated by missing variables (intangible asset value, organizational capital and unaccounted IT capital) correlated with the measured IT variable, as described in Section 2.1. In order to account for these factors, we modify equation (1) so that:

$$q_{IT}^{\ *} = \beta + \psi(\sigma_{IT}), \tag{6}$$

where $\beta > 1$ reflects the complementary missing variables, while $\psi(\sigma_{IT})$, as defined in equation (1) captures the component of the required rate of return attributed to the opportunity cost of exercising investment options. Thus, the market value specification should yield marginal *q* of IT consistent with the form specified in equation (6).

Accordingly, we introduce IT risk into the market value regression by adding an interaction term between IT capital and IT risk, denoted $IT \times \sigma_{IT}$, so that the estimated regression model is as follows:

$$\begin{aligned} TV_{lt} = {} & \beta_0 + \beta_1 IT_{lt} + \beta_2 K_{lt} + \beta_3 OA_{lt} + \beta_4 RD_{lt} + \beta_5 Ad_{lt} + \beta_6 IT_{lt} \times \sigma_{IT,lt} \\ & + \beta_7 IndReg_l + \beta_8 IndCap_l + \beta_9 IndQ_l + \beta_{10} IndConc_l + \sum_{t=1987}^{1994} \beta_t Year_t + \varepsilon_{lt}. \end{aligned} \quad (7)$$

In equation (7), the marginal *q* of IT capital is then $\beta_1 + \beta_6 \sigma_{IT}$, which is a first-order linear approximation to the theoretically predicted form of marginal *q* in equation (6). Recall that the IT risk measure, σ_{IT}, is estimated at the industry segment level using equation (3), as detailed in Section 3.1. Consistent with our options pricing arguments, we predict that β_6 should be positive. We further predict that controlling for IT risk will reduce the direct IT return coefficient β_1, with the magnitude of reduction reflecting the risk premium component of gross IT valuations.

In our analysis, we first report OLS results for all of the regressions. We also report the results of alternative empirical specifications, including robustness checks for heteroskedasticity, within-firm correlation, endogeniety (2SLS), alternative IT risk measure, and heterogeneity of earnings variability, finding in all cases that the qualitative nature of the results is consistent with the benchmark OLS regressions.

3.3. Data

We obtain firm-level IT stock data from the Computer Intelligence Infocorp (CII) installation database, generally regarded as the most authoritative source of data on IT investments by companies. This data source covers the years 1987-1994, and includes data on over 500 *Fortune 1000* firms. A firm's IT capital stock includes all firm-level computer systems including mainframe CPUs, peripherals, minicomputers, and PCs. Accounting and financial data are derived from the Compustat database. Stock market returns and valuation data are obtained from a database maintained by the Center for Research in Security Prices (CRSP) maintained by the University of Chicago. To be consistent with prior literature, current dollar variables are used in the market value analyses (see, e.g., Brynjolfsson et al. 2002) and constant dollar variables are used in the production function analyses (see, e.g., Dewan and Min 1997).[6]

Summary statistics of the final sample are presented in Table 1. Our sample consists of 4,228 firm years, with the exception that the standard deviation of stock returns has 183 fewer values due to missing daily stock returns data from CRSP. Looking at the descriptive statistics in Table 1, note that the mean level of IT capital stock in the database is approximately $26 million. The magnitude of IT stock held by companies in the database encompasses a wide range, with the smallest being $210,000 while the largest is over $250 million. The range of non-IT capital accumulated by a firm varies from $16.68 million to $21.8 billion, with a mean of $2 billion. The average total firm value of our sample is $10.8 billion, indicating that the firms in our database are large firms. Most of the variables have standard deviations greater than their respective means. The large variations in variable values are likely to enhance the power of the regression analyses.

To estimate IT Risk using equation (3), we partition the sample into industry segments. Each two-digit SIC industry having less than roughly 150 observations is combined with other two-digit industries with insufficient observations that share the same one-digit SIC. One exception to this grouping criteria is firms with a two-digit SIC code greater than 80. Since there are only 45 such firms, they are categorized into one group. This grouping procedure yields 17 broadly defined industries, similar to the "one-and-a-half-digit SIC" industry classification of Brynjolfsson et al. (2002). Table 2 provides a listing of the resulting 17 industry segments, including the primary two-digit SIC codes in each segment and a brief de-

[6] To convert to constant 1990 dollars, we use the same deflators used in prior IT and productivity research. The reader is referred to Dewan and Min (1997) for details. As a robustness check we generate production function results using current dollar denominated variables, finding that the results are qualitatively similar to those obtained using constant dollars.

scription. In most cases, industry segments contain single or closely related two-digit SIC codes. [7] As is evident from the table, the firms in our study come from a wide range of manufacturing and service industries.

4. Empirical Results

4.1. IT Risk

To examine the riskiness of IT investment, we first estimate equation (2) based on the pooled sample and report the results in Table 3. The table presents two sets of estimations, with stock-returns variability (Panel A) and earnings variability (Panel B) as the dependent variables, using three different industry controls: (i) 9 one-digit SIC dummies, (ii) 46 two-digit SIC dummies, and (iii) Inclusion of four industry structure variables defined at the two-digit SIC level, described in Section 3.1.

The coefficient of IT capital is positive and significant at the 1% level in all six regressions. On the other hand, the estimated coefficients for non-IT capital vary somewhat in sign and significance across the various specifications. In all cases, the coefficient of IT capital dominates the coefficient of non-IT capital in terms of magnitude and significance. An *F* test for the difference in magnitude of these two coefficients is significant at the 1% level in all cases. The control variables have the expected signs. The four industry structure variables are significant as a group at the 1% level. Taken together, Table 3 indicates that IT investments account for a significant portion of overall firm risk, and that the riskiness of IT capital investment is significantly higher than that of non-IT capital investment on average. Since the qualitative nature of the results using alternative industry controls is similar, in the interest of brevity, subsequent analyses are tabulated based on the four industry structure variables only.

Table 4 presents our estimates of IT risk coefficients at the industry segment level from equation (3). When using stock returns variability as the risk measure, we find that 8 out of the 17 industries have significant positive IT coefficients (IT investments associated with higher firm risk), another 7 industries have statistically insignificant coefficients (indeterminate relationship between IT investments and firm

[7] We recognize that diversified firms might operate in multiple two-digit SIC codes, however, for the sake of tracta-

risk), and 2 industries have significant negative IT coefficients (IT investments associated with reduced firm risk). Overall, durable goods manufacturing, retail and wholesale trade, and financial services tend to have the highest IT risk. Interestingly, these sectors match closely with the six industry segments — Computer Manufacturing, Telecommunications, Semiconductors, Retail, Wholesale and Securities — identified by McKinsey Global Institute (MGI 2001) as having simultaneously the highest jump in both labor productivity and IT capital intensity between the 1987-1995 period on average and the 1995-99 time frame. At the same time, our finding that IT investments are associated with reduced firm risk in some industries is consistent with the analysis of Hunter et al. (2003), who argue that in some environments IT investments can lead to earnings stabilization and reduced firm risk. We obtain qualitatively similar results using earnings variability as the alternative dependant variable. Section EC.2 and Table EC.1 of the Online Appendix demonstrate that the IT risk estimates from equation (3) are robust to alternate specifications of industry heterogeneity.

4.2. Risk vs. Return of IT Investments

4.2.1. Production Function Analysis

The production function analysis does not require additional accounting and stock returns data, so the data for this analysis are drawn from the CII database, consisting of 6,036 firm-year observations for the period 1987-1994. We consider two sets of subsample partitions based on the industry average IT risk estimates derived from stock returns and earnings variability, respectively. Recall that the High IT Risk sample comprises of the industry segments with positive and significant IT risk estimates in Table 4, while the Low IT Risk sample consists of industry segments for which the IT risk estimates are negative and significant. Industries with insignificant IT Risk coefficient estimates are left out of the analysis, since it is not clear whether to classify them as High or Low IT Risk. Section EC.3 and Table EC.2 of the Online Appendix provide some descriptive statistics for the production function subsamples.

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bility we only consider the primary two-digit SIC code in assigning firms to industry segments.

Table 5 summarizes the results of the production function analysis obtained by estimating regression model (4) separately for the High and Low IT Risk samples, respectively. The elasticity of IT capital for the average High IT Risk firm, as measured by the coefficient on Log(IT), is roughly four times as large as that for the average Low IT Risk firm. The marginal product of IT, which is defined as IT elasticity divided by IT factor share (*IT/VA* in Table EC.2), is also substantially higher for the High IT Risk firm than that for the Low IT Risk firm, on average. Firms in high IT risk industries invest more in IT and accrue a higher marginal return. Overall, the evidence lends support to the argument that the higher the IT risk, the higher the lost option value of IT investments, and consequently the higher the return on IT investments, all else being equal. In addition, the coefficients of non-IT capital and labor for the two samples are similar in both magnitude and statistical significance, suggesting that IT risk affects the productivity of IT inputs only, and not that of non-IT factors of production. We obtain similar results when we conduct the sample splits based on IT risk estimates derived from the earnings variability regression.[8]

We applied a variety of robustness checks to the production function analysis. The results are reported in Table 6, using variations on the baseline analysis in Table 5 for the stock returns variability risk measure. Prior research by Anderson et al. (2004) has demonstrated significant lagged effects, wherein IT capital spending affects earnings in the future. Note that this study measure IT investment using IT capital stock that reflects cumulative IT investments. As a result, our analysis already captures the lagged effects of IT investments. Still, since our dependent variable is annual value added, we conduct a lagged analysis to assure that our baseline (non-lagged) estimates are not biased in any way. In particular, in equation (4) we replace IT and non-IT capital variables in year t with one-year lagged values of the IT capital and non-IT capital measures respectively, keeping all other variables intact. As the first two columns of Table 6 indicate, the qualitative nature of the subsample analysis using lagged capital variables is qualitatively

[8] In response to an anonymous reviewer's suggestion, we conducted a comparative analysis of high versus low IT intensity subsamples, which we took to be the top and bottom thirds of the data, based on IT factor share. We estimated IT output elasticities of 0.093 and 0.042 for the high and low IT intensity subsamples, respectively. We also found the high IT intensity subsample to have a substantially higher average IT risk coefficient of 0.067, as com-

similar to the baseline case of Table 5. Another concern in production function specifications of this kind is endogeneity of the IT capital stock variable, perhaps due to the lagged effects described above. To allay this concern, we conduct two stage least squares regressions, using as instruments one year lagged value of IT capital along contemporaneous values of all other independent variables. We find that the nature of the results is essentially unchanged.

The next two columns in Table 6 show the results for an alternative subsample definition. Recall that the High Risk subsample is much larger than the Low Risk subsample, which contains just two industry segments. For more balanced partition of subsamples, we only include industry segments with positive IT risk estimates significant at the 1% level. At the same time, we increase the size of the Low Risk subsample by including all industry segments with a negative estimated IT risk coefficient, independent of significance level. The results for this alternative subsample definition are qualitatively similar to the baseline case of Table 5.

The final robustness check considers an alternative definition of the IT risk measure derived from the standard deviation of return on equity (ROE, defined as the ratio of annual earnings to shareholders' equity). We reran the IT risk regression of equation (3) using the standard deviation of ROE as the dependent variable, and conducted the production function analysis on the resulting high and low IT risk subsamples. As the final two columns of Table 6 indicate the results again are qualitatively similar to the baseline case. Overall, we conclude that the production function results are robust to alternative specifications and estimation methods.

4.2.2. Market Value Analysis

The results of pooled market value regressions with and without the IT risk variables are reported in Table 7. Panel A contains the results for the case in which IT risk measures are estimated based on stock returns variability, while Panel B is based on earnings variability. Column (1) reports the results corresponding to equation (5) where IT risk term is omitted. Recall our argument in Section 3.2.2 that the theo-

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pared to -0.309 for the low IT intensity subsample. Thus, high IT risk and high IT returns go together, consistent retical basis for incorporating IT risk in the market value regression is to add an IT risk interaction term, $IT \times \sigma_{IT}$, as specified in equation (7).[9] The results for this case are reported in Column (2). To check the sensitivity of our results to model specification, we also run alternative regressions that include IT risk only (Column 3) and both IT risk and the IT risk interaction term (Column 4).

Several observations emerge from Panel A of Table 7. First, in the absence of IT risk (Column 1), the IT coefficient is equal to 14.606, and is significant at the 1% level. The magnitude of the IT coefficient is consistent with the IT estimates reported by Brynjolfsson et al. (2002), as are the sign and significance of the other variables in the regression. Second, after adding the IT risk interaction term $IT \times \sigma_{IT}$, the IT coefficient remains significant but decreases substantially to 9.919, a 32% decline in magnitude.[10] In addition, the IT risk interaction term is positive and significant at the 1% level. Third, when we add the IT risk variable only (see Column 3), the IT risk term is positive and significant. However, the decline in the positive and significant IT coefficient is somewhat lower. Fourth, when both IT risk and the IT risk interaction term are added (Column 4), only the interaction term is positive and significant.[11] The insignificance of the IT risk variable itself also indicates that it does not have incremental explanatory power beyond the IT risk interaction variable, further corroborating the soundness of the model specification of equation (7) that introduces IT risk through the interaction term in the market value regression.

It is worth noting that the IT coefficients remain substantially greater than unity even after controlling for IT risk. As documented by Brynjolfsson et al. (2002), the high IT coefficient could result from the missing IT and organizational capital, for which we do not have explicit controls available — their effect is reflected in the direct IT coefficient β_1 still being substantially greater than unity. We obtain qualita-

with our overall risk-return argument.

[9] Note that we have dropped the subscript "*lt*" here, and in Tables 7-8, for the sake of brevity.

[10] When we add into the regression model (7) a non-IT risk interaction term, $K * \sigma_K$ (where σ_K is the industry average risk estimate of non-IT capital), the coefficient on IT is 10.37, significant at the 1% level. This indicates that the risk of non-IT capital has little effect on our IT return estimate, thereby justifying the exclusion of non-IT risk from our regression analyses.

[11] The Pearson correlation between IT risk and the IT risk interaction term is 0.314, significant at the 1% level, so perhaps multicollinearity between the two terms rendered the IT Risk term to be insignificant.

tively similar results in Panel B of Table 7 when we use the IT risk estimates generated from the earnings variability regression.

We conduct a variety of robustness checks of the market value analysis, with the results reported in Table 8. Taking as the baseline case the OLS estimates for the stock returns variability specification with the IT risk interaction term (Column 2 in Panel A of Table 7), we consider five different variations. In each case, we report the results without and with the IT risk interaction term. The first check concerns possible heteroskedasticity of the error terms. In Table 8 we report the results based on White's corrected standard errors. Note that this does not change the point estimates of the coefficients, just their standard errors (and possibly significance levels). As can be seen, the results are essentially unchanged.

Over the eight-year sample period, many firms appear multiple times in the data. To the extent that observations for a given firm are correlated, there is serial correlation in the residuals and consequently OLS standard errors (t-statistics) are underestimated (overstated). To alleviate the concern of within-firm correlation of the residuals, we adopt the Fama-MacBeth (1973) procedure. The Fama-MacBeth standard errors are widely used in the accounting and finance fields to deal with the lack of independence because of multiple observations per firm (see, e.g., Teoh et al. 1998, Guo et al. 2006).[12] Specifically, we conduct a year-by-year cross sectional market value regression of equation (7). Overall statistics are then computed by averaging the time series of estimated yearly coefficients and t-statistics. Table 8 presents the time-series coefficient averages of eight yearly cross-section regressions with and without IT risk variables. T-statistics in square brackets are computed as $\mu(t_y)/[\sigma(t_y)/\sqrt{Y-1}]$, where t_y is the t-statistic from the regression of year y, $\mu(t_y)$ and $\sigma(t_y)$ is the mean and standard deviation of t-statistics of yearly cross-sectional regressions from 1987 to 1994, and Y is the number of cross-sectional regressions, which is equal to 8 in our case. It is evident that the magnitudes and significance levels of IT and non-IT variables

[12] The mean and median of the number of observations per firm for our panel data is 5.4 and 7, respectively. More than 25% of the sample firms have no more than 2 years of data. So, the panel is too imbalanced to implement a sophisticated lag structure.

are very similar to those of the baseline case of Table 7, suggesting that within-firm correlation is not a serious problem.

The next robustness check examines potential problems due to endogeneity. We conduct two stage least squares regressions, treating IT capital and the IT risk interaction term as endogenous (using one year lagged endogenous variables and all other independent variables as the instruments). The qualitative nature of the results is similar to the baseline case. We also considered an alternative IT risk measure, derived from the standard deviation of ROE. Again, the nature of the results is unchanged.

Finally, we considered the potential impact of heterogeneity in earnings variability across industries, and the possibility that the results might be driven by the industries with the greatest dispersion in this variable.[13] To allay this concern, we conducted a restricted subsample analysis of the market value regression, based on *SD (Earnings)* as the risk measure. Specifically, we re-estimated the risk and market value regressions of equations (3) and (7) after dropping five two-digit SIC industries with the highest average *SD (Earnings)*, amounting to a total of 115 observations. The results with and without the IT Risk term for the market value regressions are reported in Table 8. Clearly, the qualitative nature of the results is unchanged. If anything, the results are stronger as indicated by a nearly 50% reduction in the IT coefficient after incorporating the IT risk term.[14]

To summarize, the market value analyses generate consistent and robust evidence that IT risk is positively associated with firm value, and that incorporation of IT risk significantly reduces the IT coefficient. The positive association between IT risk and market value is consistent with the real options perspective on IT investment. That is, IT risk positively impacts the opportunity cost of IT investment options, and therefore it contributes positively to gross IT returns. The role of IT risk in IT returns can be seen to be an important reason for the seemingly excessive IT returns documented by prior studies.

5. Conclusions

[13] We thank an anonymous reviewer for raising this issue.
[14] We also conducted additional outlier analysis by dropping influential observations based on Cook's D and DFFITS criteria (see, e.g., Greene 1993), and again found that the qualitative nature of the results is unchanged.

In this paper, we have developed empirical measures of IT risk and incorporated them into the two most widely used frameworks for analyzing IT returns: production function and market value specifications. Our analysis is guided by the options theory of irreversible investment, wherein IT capital investments are viewed as the exercise of call options. The main thrust of the empirical analyses is on understanding the magnitude of IT risk and on quantifying the risk-adjusted returns on IT investment. Our key findings are that IT investments are riskier than other types of capital investments, and that IT returns are associated with a substantial risk premium.

An obvious practical implication of our results is that managers should apply a higher hurdle rate of expected returns when investing in IT assets, as compared to other types of capital investments. The common practice of simply applying the weighted average cost of capital in the capital budgeting of all types of assets (e.g., Dixit and Pindyck 1995), irrespective of their risks, might be misguided when applied to IT capital investments. Such a practice will on average apply a discount rate that is too low given the riskiness of IT investments, overstating the discounted present value of the investments, and leading to the funding of IT projects whose incremental returns do not justify the added risks. While the risks of IT investments are well-recognized, this is one of the first empirical scientific studies to shed light on the magnitude of IT risk and the nature of the risk-adjusted return to IT investment.

Our research makes several important contributions. First, we develop a method for operationalizing the empirical measurement of IT risk, as captured in the variability of stock returns and earnings. While the relationship between risk and return is well understood from the economics and finance literatures, it has not yet been introduced into studies of the payoff from IT investment. Our research suggests a way in which IT risk can be measured, and proceeds to use the IT risk estimates to understand how it influences the payoff from IT investment. From an investment perspective, it is extremely important to develop an increased understanding of how technology risk is manifested in cash flows and how it could be managed.

Another contribution of this research is as a potential explanation for the excessive returns on IT investment documented in recent research in the IT investments literature, complementing alternative explanations that have already been put forward, such as the adjustment costs of introducing technology into a firm and unmeasured investments in organizational capital that are highly correlated with IT capital. This paper provides another explanation, namely, the risk premium associated with the riskiness of IT investments inflates gross measures of IT returns. Indeed, our results suggest that roughly 30% of the gross return on IT investment corresponds to the risk premium associated with IT risk.

Finally, our results provide new insights into the value derived from incorporating an options approach to decision making related to IT investments. While much of the real options research in the information systems literature focuses on the creation of options (such as expansion or abandonment of IT projects), it should also be recognized that investment in IT capital can itself be viewed as the exercising of a call option with the attendant opportunity costs. These costs are a result of the lost value of the option to wait to make the investment in the future when the uncertainty about costs or benefits might be lower. This is not to imply that it is always optimal to wait, but rather that timing considerations be included in a financial assessment of the investment decision. Furthermore, we know that the value of the real options associated with capital investment is an increasing function of the average risk of the investment, making it critical to account for the option value of these riskier investments.

This research is not without limitations. We use an industry segment level proxy measure of IT risk, which is likely to understate IT risk at the firm level, on average. Another limitation is that our dataset ends in 1994, so our results do not speak directly to the post-1994 period. Specifically, it would be extremely interesting to understand how the adoption of the Internet and electronic business is affecting the risk-return profile of firms (see Dewan and Ren 2007 for an event study approach). Finally, we only have aggregate measures of IT capital stock, which limits our ability to understand how the profile of IT investments across assets and applications affects IT risk.

There are many avenues for further research. First, we hope that our research leads to future work that further refines the measurement of IT risk at the individual firm level, perhaps using suitable survey methods. In particular, studies that examine the risk profile of the portfolio of IT projects within a firm, and relate them to aggregate measures of risk at the firm level, such as ours, would be extremely valuable in more fully understanding the determinants of overall IT risk (see, e.g., Bardhan et al. 2004 for a real options analysis of IT portfolios). In addition, there is a need for further enhancing our understanding of the risk-return profile of different classes of IT investment, by building on the leading efforts in the literature to date, examples of which are: the empirical study of the costs and benefits of ERP adoption by Hitt et al. (2002); modeling of the adoption incentives for Internet-based procurement systems by Kauffman and Mohtadi (2004); and the analysis of investments in middleware and other types of IT infrastructure by Dai et al. (2007).

An illuminating approach for addressing some of these issues would be to conduct in-depth analyses of company field and case studies, like the analysis of the timing of deployment of the Yankee 24 electronic point-of-sale banking network by Benaroch and Kauffman (1999, 2000), the discussion of a staged adoption of an ERP system (Taudes et al. 2000), or the acquisition of CASE tools to manage risks in a software project (Kumar 2002). These case studies illustrate the options approach to analyzing IT investments, although for the most part they are restricted to managerial flexibilities around the deployment of a single IT project or investment. There are case studies and empirical analyses of a broader class of irreversible capital investments, in assets such as natural resources, nuclear power plants, offshore petroleum leases, and the like (see Schwartz and Trigeorgis 2001, Sections VI and VII), but we have been unable to find any in the IT context. In light of our results, it would be interesting to see similar analyses of irreversible IT capital investments, to illustrate the value of the real options perspective in analyzing such investments.

Finally, as mentioned above, it would be worthwhile to examine a more recent data set. Subsequent to the 1987-1994 time frame covered by the present data set, IT investments have continued to grow, are more complex, and are increasingly inter-organizational focusing on customer and supplier interactions relative to earlier periods when they focused more on internal applications (MGI 2001). It is reasonable to conclude that IT investments have not become any less risky since 1994. In general, as the IT industry continues to innovate and introduce new technologies at a rapid rate, managers would benefit from conducting more sophisticated financial assessments of IT investment decisions that incorporate the riskiness of these technologies and a recognition of their option value.

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Table 1 Descriptive Statistics of Selected Variables

Variable	*Description*	*Mean*	*Std Dev*	*Minimum*	*Maximum*
SD(Returns)	Std Dev of Daily Stock Returns	0.019	0.008	0.007	0.059
SD(Earnings)	Std Dev of Earnings	0.029	0.031	0.0007	0.186
IT	IT Capital	25.91	43.76	0.21	254.05
K	Non-IT Capital	2,046	3,907	16.68	21,819
IT_asset	IT Capital / Total Assets	0.006	0.008	0.00009	0.047
K_asset	Non-IT Capital / Total Assets	0.334	0.235	0.005	0.850
OA	Other Assets	6,024	13,815	126.24	92,156
TV	Total Firm Value	10,849	21,762	3.75	315,209
Size	Log (Market Value of Equity)	7.319	1.410	3.809	10.476
Leverage	Debt / Equity Ratio	0.191	0.145	0	0.622
RD	R&D Expenses / Sales	0.020	0.030	0	0.136
Ad	Advertising Expenses / Sales	0.021	0.030	0	0.156

Notes. All variables have 4,228 observations except that *SD(Returns)* has 4,045 observations. Please see Section 3.1 for the variable definitions. IT Capital, Non-IT Capital, Other Assets, Total Firm Value and Market Value of Equity are measured in millions of dollars. To mitigate the effect of influential observations, we winsorize all variables by setting the values in the bottom and top one percentiles to the values of the 1^{st} and 99^{th} percentiles, respectively (as in Kothari et al. 2002).

Table 2 Industry Segments in the Estimation of IT Risk

Industry Segment Code	Primary Two-Digit SIC Codes	Description	N
IND1	10,13	Mining and Extraction	147
IND2	20	Food and Kindred Products	183
IND3	26	Paper and Allied Products	146
IND4	28	Chemicals and Allied Products	373
IND5	29	Petroleum Refining and Related Industries	452
IND6	35	Industry and Commercial Machinery and Computers	262
IND7	36	Electrical and Electronic Equipment	223
IND8	37	Transportation Equipment	177
IND9	33-34,38	Metal Products and Instruments	497
IND10	49	Electrical, Gas and Sanitary Services	213
IND11	40-48	Transportation and Communication	246
IND12	50-55	Retail and Wholesale Trade	414
IND13	60	Depository Institutions	457
IND14	63	Insurance Carriers	170
IND15	61-62, 64	Security and Insurance Brokers and Services	75
IND16	73	Business Services	148
IND17	80-87	Health and Other Services	45

Notes. This partition is derived from a sample of 4,228 observations, using standard deviation of earnings as the firm risk measure.

Table 3 Pooled IT Risk Regressions

Panel A: Dependent Variable is Stock Returns Variability			
	Industry Controls		
Variable	One-Digit SIC Dummies	Two-Digit SIC Dummies	Industry Structure Variables
IT_asset	0.126*** (0.018)	0.259*** (0.0231)	0.125*** (0.017)
K_asset	-0.002*** (0.0008)	0.006*** (0.001)	-0.002** (0.0009)
Size	-0.003*** (0.00009)	-0.0005*** (0.00008)	-0.003*** (0.00009)
Leverage	0.007*** (0.001)	0.018*** (0.001)	0.007*** (0.001)
RD	0.031*** (0.005)	0.022*** (0.006)	0.030*** (0.004)
Ad	0.008** (0.004)	0.017*** (0.005)	0.005 (0.004)
IndReg			0.0001 (0.0003)
IndCap			-0.003** (0.001)
IndQ			-0.0003 (0.0002)
IndConc			0.0008*** (0.0002)
Adj R^2	0.885	0.859	0.885
N	4045	4045	4045
Panel B: Dependent Variable is Earnings Variability			
	Industry Controls		
Variable	One-Digit SIC Dummies	Two-Digit SIC Dummies	Industry Structure Variables
IT_asset	0.485*** (0.066)	0.619*** (0.071)	0.567*** (0.063)
K_asset	0.005* (0.003)	0.016*** (0.003)	0.008** (0.003)
Size	-0.004*** (0.0004)	-0.0008** (0.0003)	-0.004*** (0.0004)
Leverage	0.007* (0.004)	0.028*** (0.004)	0.009** (0.004)
RD	0.166*** (0.018)	0.182*** (0.020)	0.182*** (0.017)
Ad	0.013 (0.017)	0.048** (0.020)	0.012 (0.016)
IndReg			-0.012*** (0.001)
IndCap			0.010** (0.005)
IndQ			0.0003 (0.0006)
IndConc			-0.006 (0.005)
Adj R^2	0.550	0.539	0.546
N	4228	4228	4228

Notes. The regression specification underlying these results is that of equation (3), where panels A and B correspond to cases where the dependent variable firm risk is proxied by *SD(Returns)* and *SD(Earnings),* respectively. All variables are as defined in Table 1. Coefficients on industry and year dummies and the subscript "*It*" are omitted in the table. Standard errors are in parentheses. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Estimation of IT Risk at the Industry Segment Level

	Dependent Variable	
Variable	Stock Returns Variability	Earnings Variability
IT_asset * IND1	0.011 (0.040)	-0.196 (0.164)
IT_asset * IND2	0.172 (0.131)	0.554 (0.490)
IT_asset * IND3	0.127*** (0.029)	-0.076 (0.120)
IT_asset * IND4	-0.309*** (0.089)	-0.806*** (0.353)
IT_asset * IND5	0.035*** (0.012)	0.211*** (0.050)
IT_asset * IND6	0.028*** (0.006)	-0.017 (0.024)
IT_asset * IND7	0.162*** (0.034)	0.596*** (0.133)
IT_asset * IND8	-0.052 (0.060)	0.266 (0.244)
IT_asset * IND9	-0.030 (0.037)	0.440*** (0.147)
IT_asset * IND10	-1.188*** (0.250)	-0.957 (0.971)
IT_asset * IND11	0.159*** (0.041)	0.339** (0.137)
IT_asset * IND12	0.094** (0.045)	-0.198 (0.173)
IT_asset * IND13	0.074 (0.207)	-4.599*** (1.330)
IT_asset * IND14	0.065*** (0.022)	0.221** (0.089)
IT_asset * IND15	0.282 (0.185)	3.673*** (0.760)
IT_asset * IND16	0.066** (0.033)	0.018 (0.105)
IT_asset * IND17	-0.006 (0.065)	1.902*** (0.241)
K_asset	-0.003*** (0.0009)	0.007** (0.004)
Size	-0.003*** (0.00009)	-0.005*** (0.0004)
Leverage	0.007*** (0.001)	0.006 (0.004)
RD	0.035*** (0.005)	0.194*** (0.018)
Ad	0.004 (0.004)	0.004 (0.017)
Adj R^2	0.888	0.555
N	4045	4228

Notes. These results correspond to the estimation of regression equation (3). The 17 industry dummies are defined based on the industry classification in Table 2. All other variables are as defined in Table 1. Standard errors are in parentheses. The four industry structure variables and year dummies and the subscript "*lt*" are omitted in the table for expositional brevity. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 5 Production Function Estimates

	IT Risk Based on Stock Return Variability		IT Risk Based on Earnings Variability	
Variable	Low IT Risk Sub-sample	High IT Risk Subsample	Low IT Risk Sub-sample	High IT Risk Subsample
Log (IT)	0.020* (0.011)	0.094*** (0.008)	0.017 (0.013)	0.098*** (0.009)
Log (K)	0.277*** (0.012)	0.197*** (0.009)	0.238*** (0.016)	0.257*** (0.011)
Log (L)	0.632*** (0.014)	0.666*** (0.012)	0.685*** (0.019)	0.607*** (0.016)
IT Marg. Prod.	1.33	3.36	1.21	4.08
Adj R^2	0.926	0.860	0.944	0.869
N	969	3258	562	2535

Notes. The four industry structure variables and year dummies and the subscript "*lt*" are omitted in the table for expositional brevity. The IT marginal product is calculated as the ratio of IT output elasticity to IT factor (IT/VA). Standard errors are in parentheses. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Robustness Checks for the Production Function Analysis

	Lagged Effects (One year lagged capital variables)		Endogeneity Check (2SLS Regression)		Alternative Subsample Definition		Alternative IT Risk Measure (Based on Std Dev of ROE)	
Variable	Low IT Risk Sub-sample	High IT Risk Subsample	Low IT Risk Sub-sample	High IT Risk Subsample	Low IT Risk Sub-sample	High IT Risk Subsample	Low IT Risk Sub-sample	High IT Risk Subsample
Log (IT)	0.016 (0.012)	0.084*** (0.009)	0.014 (0.014)	0.098*** (0.009)	0.040*** (0.008)	0.076*** (0.009)	0.029*** (0.010)	0.055*** (0.012)
Log (K)	0.263*** (0013)	0.188*** (0.010)	0.294*** (0.013)	0.190*** (0.010)	0.220*** (0.009)	0.254*** (0.012)	0.174*** (0.012)	0.166*** (0.018)
Log (L)	0.653*** (0.014)	0.686*** (0.012)	0.630*** (0.015)	0.675*** (0.013)	0.674*** (0.011)	0.638*** (0.016)	0.734*** (0.016)	0.758*** (0.021)
Adj R^2	0.930	0.865	0.935	0.865	0.928	0.886	0.896	0.916
N	823	2738	823	2738	2120	2305	1281	920

Notes. The results from alternative empirical specifications: lagged effects, 2SLS regression, alternative subsample definition, and alternative IT risk measure. In the Lagged Effects specification Log (IT) and Log (K) are one-year lagged variables. Differences in sample size are due to additional data screening procedures required by alternative specifications. The four industry structure variables and year dummies and the subscript "*lt*" are omitted in the table for expositional brevity. Standard errors are in parentheses. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 7 Pooled Market Value Regressions

	Panel A: IT Risk Based on Stock Return Variability			
Variable	Without IT Risk (1)	With $IT \cdot \sigma_{IT}$ (2)	With σ_{IT} (3)	With $IT \cdot \sigma_{IT}$ and σ_{IT} (4)
IT	14.606*** (2.396)	9.919*** (2.622)	12.252*** (2.473)	10.077*** (2.626)
K	1.480*** (0.028)	1.511*** (0.029)	1.501*** (0.028)	1.512*** (0.029)
OA	1.006*** (0.007)	1.006*** (0.007)	1.007*** (0.007)	1.006*** (0.007)
$IT \cdot \sigma_{IT}$	--	36.351*** (8.355)	--	27.895** (11.391)
σ_{IT}	--	--	1166.160*** (310.435)	461.950 (423.025)
RD	Positive***	Positive***	Positive***	Positive***
Ad	Positive***	Positive***	Positive***	Positive***
Adj R^2	0.953	0.953	0.953	0.953
N	4045			
	Panel B: IT Risk Based on Earnings Variability			
Variable	Without IT Risk (1)	With $IT \cdot \sigma_{IT}$ (2)	With σ_{IT} (3)	With $IT \cdot \sigma_{IT}$ and σ_{IT} (4)
IT	13.198*** (3.232)	6.687** (3.252)	9.958*** (3.286)	6.914** (3.272)
K	1.780*** (0.038)	1.799*** (0.038)	1.816*** (0.038)	1.797*** (0.038)
OA	1.285*** (0.010)	1.301*** (0.010)	1.288*** (0.010)	1.301*** (0.010)
$IT \cdot \sigma_{IT}$	--	17.025*** (1.634)	--	17.684*** (1.938)
σ_{IT}	--	--	397.719*** (79.137)	-58.761 (92.977)
RD	Positive***	Positive***	Positive***	Positive***
Ad	Positive***	Positive***	Positive***	Positive***
Adj R^2	0.927	0.929	0.927	0.929
N	4228			

Notes. The regression specification underlying these results are the market value specifications of equations (6) and (8), without and with the IT risk variables of equations (6) and (8), respectively. Panels A and B correspond to the IT risk variable σ_{IT} derived from stock returns and earnings variability, respectively. All other variables are as defined in Table 1. The four industry structure variables and year dummies and the subscript "*it*" are omitted in the table for expositional brevity. Standard errors are in parentheses. The superscripts ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 8 Robustness Checks for Market Value Analysis

	Heteroskedasticity Check (White's Corrected Std Errors)		Within Firm Correlation Check (Fama MacBeth Regressions)		Endogeneity Check (2SLS Regressions)		Alternative IT Risk Measure (Based on Std Dev of ROE)		Heterogeneity of Earnings Variability (Restricted Subsample)	
Variable	w/o IT Risk	w/ IT Risk	w/o IT Risk	w/ IT Risk	w/o IT Risk	w/ IT Risk	w/o IT Risk	w/ IT Risk	w/o IT Risk	w/ IT Risk
IT	14.606*** (3.754)	9.919*** (3.497)	16.286*** [5.543]	11.592*** [4.498]	13.743*** (3.042)	6.794** (3.442)	12.626*** (3.148)	9.993*** (3.169)	12.290*** (3.341)	6.457* (3.353)
K	1.480*** (0.051)	1.511*** (0.052)	1.496*** [25.222]	1.528*** [23.468]	1.522*** (0.032)	1.567*** (0.034)	1.768*** (0.038)	1.804*** (0.038)	1.835*** (0.039)	1.810*** (0.039)
OA	1.006*** (0.012)	1.006*** (0.012)	0.991*** [16.793]	0.990*** [16.677]	1.002*** (0.008)	1.002*** (0.008)	1.242*** (0.009)	1.227*** (0.010)	1.286*** (0.010)	1.305*** (0.010)
$IT \cdot \sigma_{IT}$		36.351*** (13.892)		34.623*** [4.938]		45.366*** (10.468)		2.188*** (0.384)		19.808*** (1.997)
RD	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***
Ad	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***
Adj R^2	0.953	0.953	0.956	0.956	0.953	0.953	0.937	0.938	0.927	0.927
N	4045	4045	Average 505	Average 505	3296	3296	3773	3773	4085	4085

Notes. Results for alternative empirical specifications of the market value regression of Equation (8): (i) heteroskedasticity-adjusted results; (ii) within firm correlation check using the Fama MacBeth regression; (iii) endogeneity check using 2SLS regression; and (iv) alternative IT risk measure, based on standard deviation of ROE; (v) robustness to heterogeneity in earnings variability with *SD(Earnings)* as the risk measure. The four industry structure variables and year dummies and the subscript "*lt*" are omitted in the table for expositional brevity. Standard errors are in parentheses, except for the Fama MacBeth regression where average *t* statistics from the yearly regressions are in the square brackets. The superscripts ***, ** and * denote significance at 1%, 5% and 10%, respectively.

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Additional Tables and Discussion

This online appendix provides additional discussion and tables in support of the analysis in the main body of the paper.

EC.1. Theory of Irreversible Investment Under Uncertainty

Our starting point is the analysis of Dixit and Pindyck (1994), suitably adapted to the goals of our subsequent empirical analysis. Consider a firm that is evaluating investment in a project, whose cost I is fixed,[1] but whose value V, the present value of future incremental cash flows, follows a stochastic process over time. The investment decision is that of timing the investment, in terms of determining the threshold value of V, denoted by V^*, at which point the firm should trigger the investment. The simple NPV rule would be to invest when $V \geq I$, so that V^* is equal to the direct cost of investment I. This rule ignores the opportunity cost of the lost option value to wait, so it is incorrect in general.

Dixit and Pindyck (1994, Chapter 5, pp. 138-139) analyze the optimal threshold V^* under the assumption that V follows a geometric Brownian motion,[2] $dV = \alpha V dt + \sigma V dz$, where dz is the increment of a Wiener process, α is the drift parameter representing the expected percentage rate of change of V, and σ is the variance parameter. This implies that over any interval Δt, the change in V, denoted ΔV, is normally distributed with mean $\alpha\,\Delta t$ and variance $\sigma^2\,\Delta t$. The firm's investment opportunity is akin to a perpetual call option on a dividend paying stock, with the dividend on the stock being analogous to the revenue stream generated by the completed project. It is assumed that the risk-adjusted return on the project, denoted by μ, is greater than the value growth parameter α, otherwise the firm would never make the

[1] We show below that the results are unchanged if the cost I is assumed to decline over time, following IT cost trends.

[2] The qualitative nature of the results are unchanged when alternative stochastic processes are considered, such as a mean-reverting process and a mixed Brownian motion/jump process.

investment, holding onto its call option forever.[3] The difference $\delta = \mu - \alpha > 0$, corresponds to the dividend or revenue portion of the risk-adjusted return on investment, and represents the opportunity cost of keeping the option to invest alive.

We refer the reader to Dixit and Pindyck (1994, Chapter 5) for the detailed contingent claims analysis of this problem. The basic idea is that the value of the option to invest is increasing in the uncertainty parameter σ and decreasing in the dividend parameter δ, so that the choice of V^* must strike a balance between the opportunity cost of exercising the option, embodied by the uncertainty parameter σ, and the opportunity cost of keeping the option alive, characterized by the dividend parameter δ. The optimal value threshold can be expressed as follows:

$$V^* = (1+\psi(\sigma))\ I, \tag{EC1}$$

where the option-value "wedge," $\psi(\sigma)$, between the optimal investment rule and the simple NPV rule is a positive and increasing function of the uncertainty parameter σ.[4] Thus, $\psi(\sigma)I$ represents the opportunity cost due to the lost option value, so that the optimal investment rule requires that the value of the project be at least as large as the sum of the direct cost *I* and the opportunity cost $\psi(\sigma)I$.

Applying the above analysis to the marginal capital investment project, it follows from equation (EC1) that the "marginal *q*" (the ratio of the increase in market valuation to the cost of the incremental project) would satisfy:

$$q^* = V^* / I = 1 + \psi(\sigma). \tag{EC2}$$

That is, the threshold $q^* > 1$. Contrary to the simple NPV rule that sets $q^* = 1$, the optimal capital stock calls for leaving the marginal *q* greater than unity in equilibrium, with the difference $q^* - 1 = \psi(\sigma)$ rep-

[3] Note that this theory allows the growth parameter α to be negative. This corresponds to the case where the value of the innovation underlying the investment opportunity declines over time, due to obsolescence say, as might be the case with some cutting edge IT applications.

resenting the (lost) option value which is increasing in the uncertainty parameter σ.[5] Qualitatively, the impact of investment risk is to raise the required or hurdle rate of return, reflecting the opportunity cost due to the lost option value of investment.

EC.2. Robustness of IT Risk Estimates to Industry Heterogeneity

In this section, we examine the robustness of the IT risk estimates to alternative specifications of industry controls in equation (3). Specifically, we would like to be assured that the IT risk estimates are not somehow biased by a potential lack of sufficient control for industry heterogeneity. Table EC.1 summarizes the IT risk coefficient estimates using five alternative industry controls in the IT risk specification with *SD(Returns)* as the firm risk measure: (1) four industry structure variables, IndReg, IndCap, IndQ and IndConc (our baseline case); (2) industry fixed effects with 17 industry dummy variables, corresponding to the industry classification of Table 2; (3) industry random effects specification; (4) separate industry-by-industry estimation of the IT risk regression; and (5) 46 industry dummies at the two-digit SIC level. The random effects approach is often preferred to the fixed effects approach (see, e.g., Greene 1993), and the separate industry-by-industry estimates removes, by construction, any unobserved between-industry heterogeneity associated with our 17 industry classification — albeit at the cost of estimation efficiency. Note further that specifications (2)-(4) are based on the 17 industry classification of Table 2, while specification (5) is a finer industry classification at the two-digit SIC level. As can be seen from Table 4, the IT risk estimates obtained from these five alternative specifications are highly consistent with each other, in terms of the sign and significance of IT risk coefficients. Indeed, the alternate IT risk estimates are highly

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[4] In more detail, $\psi(\sigma) = 1/(\beta - 1)$, where $\beta = 1/2 - (r-\delta)/\sigma^2 + \sqrt{[(r-\delta)/\sigma^2 - 1/2]^2 + 2r/\sigma^2}$ is the positive root of "the fundamental quadratic" equation in the contingent claims analysis of Dixit and Pindyck (1994). In this model, β is greater than 1 and decreasing in σ, so that $\psi(\sigma)$ is positive and increasing in σ.

[5] One might wonder how the optimal threshold q^* changes if the project cost I is declining over time, reflecting the underlying trends in IT costs. In fact, the analysis is scale independent so that the optimal threshold is not affected by changes in the cost I. Specifically, the optimal threshold q^* is only a function of the discount rate ρ, the value growth parameter α, and their difference $\delta = \rho - \alpha$, and it is not a function of the cost I (see Footnote 8). In

correlated with each other, with pair-wise Spearman correlation coefficients all significant in the 1% or 5% level (not tabulated). These results validate our choice of specification (1), following Bharadwaj et al. (1999), which includes highly comprehensive controls for any unobserved industry heterogeneity, since it captures key sources of differences across industries.[6]

EC.3. Descriptive Statistics for the Production Function Subsamples

Table EC.2 presents descriptive statistics of the variables used in the production function analysis for the sub-samples of Low vs. High IT Risk. Since the production function analysis does not require additional accounting and stock returns data, the data for this analysis are drawn from the CII database, consisting of 6,036 firm-year observations for the period 1987-1994. We consider two sets of subsample partitions based on the industry average IT risk estimates derived from stock returns and earnings variability, respectively. Recall that the High IT Risk sample comprises of the industry segments with positive and significant IT risk estimates in Table 4, while the Low IT Risk sample consists of industry segments for which the IT risk estimates are negative and significant. Industries with insignificant IT Risk coefficient estimates are left out of the analysis, since it is not clear whether to classify them as High or Low IT Risk. As is evident from Table EC.2, the two subsamples display consistent differences in both the dependent variable and independent variables. For example, the average High IT Risk firm has higher levels of value added, IT capital and labor expense than the average Low IT Risk firm.

References

Bharadwaj, A.S., S.G. Bharadwaj, B.R. Konsynski. 1999. Information technology effects on firm performance as measured by Tobin's *q. Management Science.* **45**(6) 1008-1024.

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other words, as the cost I declines, lower cost projects will be funded over time, but the optimal threshold of the ratio of marginal value to marginal cost will remain constant (and greater than unity).

[6] It is worth noting that while specification (2) is an otherwise reasonable choice for industry controls, it suffers from a multicollinearity problem and imprecision of IT risk estimates, due to the high positive correlation (average of 0.56, with $p < 0.0001$ in every case) between the 17 industry dummies and the respective 17 IT-industry interaction terms in equation (3). This is not surprising since, by construction, both sets of these variables are coded as 0 for 16 out of the 17 industries (i.e., an average of 94% of the data).

Dixit, A.K., R.S. Pindyck. 1994. *Investment Under Uncertainty,* Princeton University Press, Princeton, NJ.

Table EC.1 Robustness Check to Alternative Industry Effects Specifications

Industry Segment	(1) Four Industry Structure Variables	(2) 17 Industry Dummies	(3) Random Effects Specification	(4) Industry By Industry Estimation	(5) 46 (Two-Digit SIC) Industry Dummies
1	0.011	0.044	0.034	0.201**	0.303***
2	0.172	0.017	0.139	-0.27	0.289
3	0.127***	0.145***	0.124***	0.452***	0.211***
4	-0.309***	-0.265**	-0.317***	-0.219***	-0.136
5	0.035***	0.049***	0.036***	0.086*	0.078***
6	0.028***	0.022***	0.027***	0.067	0.030***
7	0.162***	0.238***	0.157***	0.189***	0.255***
8	-0.052	-0.164*	-0.069	-0.344***	-0.112
9	-0.030	-0.04	-0.042	-0.035	0.198***
10	-1.188***	-0.283	-1.255***	-0.662***	-0.013
11	0.159***	0.087*	0.167***	0.077*	0.080
12	0.094**	0.088	0.106***	0.120**	0.257***
13	0.074	-0.113	0.101	-0.287	-0.060
14	0.065***	0.08***	0.066***	0.331***	0.077***
15	0.282	-0.195	0.313*	0.386	1.401***
16	0.066**	0.012	0.063**	-0.033	0.091*
17	-0.006	-0.062	-0.009	-0.07	0.009

Notes. IT risk coefficient estimates for alternative specifications of industry effects in equation (3): (1) four industry structure variables, IndReg, IndCap, IndQ and IndConc; (2) 17 industry dummies; (3) industry random effects specification; (4) separate industry-by-industry estimation of the IT risk regression; and (5) 46 industry dummies at the two-digit SIC level. Note that specifications (2)-(4) are based on the industry classification of Table 2. The superscripts ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table EC.2 Descriptive Statistics for Production Function Analyses

		IT Risk Based on Stock Return Variability				IT Risk Based on Earnings Variability			
		Low IT Risk		High IT Risk		Low IT Risk		High IT Risk	
Variable	Description	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
VA	Value-Added	1534.31	1579.58	1791.87	3062.18	1447.57	1885.81	1898.35	3127.85
IT	IT Capital	21.70	27.65	34.77	63.09	18.63	28.64	33.67	61.02
K	Non-IT Capital	4698.16	5475.50	2382.92	4905.57	1767.36	3125.75	2580.81	5297.54
L	Labor	756.76	819.14	1016.63	1474.25	813.32	982.45	1043.81	1419.94
IT/VA	IT Cap / Val. Added	0.015	0.015	0.028	0.128	0.014	0.015	0.024	0.139
N	Number of Obs.	969		3258		562		2535	

Notes. The Low and High IT Risk sub-samples consist of firms of low and high IT risk industries, respectively, derived from the initial CII database of 6,036 firm-year observations for the period 1987-1994. An industry is classified as high (low) IT risk if the industry average IT risk estimate from regression (3) is positive (negative) and statistically significant at the conventional levels. The classification is based on IT risk estimates from the regression model (3) with stock returns variability and earnings variability as the dependent variable, respectively. *VA, IT, K,* and *L* are denominated in millions of constant dollars.