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Studies in IT: Capacity Utilization and Option Market Information

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Studies in IT: Capacity Utilization and Option Market Information

by

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Abstract

As Information Technology (IT) continues to be a major driving force for innovation, productivity, and economic growth, it is still crucial to understand how IT affects and transforms firms and industries - the benefits it creates as well as the risks it causes. This dissertation consists of three essays, and explores the nature and value of IT, as a production input, as an event that may contain informational content, and as an investment decision that can change firms' risk profiles. The first essay discusses IT's contribution to productive capacity - the maximum sustainable level of output that a production unit may achieve by increasing its short-run inputs to a limit. The second essay examines the informational nature of IT investment announcements - whether they provide new information to investors. The third essay investigates the risky nature of IT investment announcements - how they affect firm risk perceived by investors.

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I would like to express my sincere gratitude to Professors Barrie R. Nault and Victoria L. Mitchell, for always being patient, receptive, and supportive, and for guiding me to be a better scholar.

Dedications

To my parents, ZHANG Ke and WANG Yunfeng, and to my wife, ZHOU Shiding (Rachel).

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Chapter 1

INTRODUCTION

This thesis focuses on studying, understanding, and measuring the nature and value of Information Technology (IT). We take two different perspectives of IT, and empirically explore both. The first perspective is to view IT as a production input factor and study IT productivity under the production function framework. Under this framework, IT is used together with other inputs (e.g., labor, non-IT capital such as structures and equipment, intermediate inputs such as energy and service) plus the current level of technology by a production unit (e.g., firm, industry) to produce output. Since the late 1990's, research evaluating the contribution of IT investments to output under the production function framework has converged on a positive IT contribution (Cheng and Nault 2007). Our research explores how IT as a production input contributes to, instead of actual output, industry-level capacity output as well as to the capacity utilization (CU) rate. We adopt the capacity definition from the Federal Reserve Board - a hypothetical maximum output level by raising the levels of labor and intermediate inputs to a maximum but sustainable level.

The other perspective that we adopt to study the value of IT is to view IT as a strategic investment decision by firms. The goal is to understand the value and impact of such IT investment decisions on firms by studying the responses from option market investors to IT investment announcements. Such responses capture the collective assessment by a large number of investors of the discounted value of current and future firm performance that is attributable to the IT announcements. When an IT investment announcement is made, investors evaluate the public information contained in the announcement, and then re-adjust their beliefs about the expected value and uncertainty of the announcing firm. According to the semi-strong version of the efficient market hypothesis (Fama 1970), such "IT-induced" re-adjustments in beliefs about firms' value and risk lead to immediate trading actions on firms' securities, and thus to a change in characteristics of the securities such as price, trading volume, and volatilities. Dawei Zhang has done the majority of the writing, and is the primary contributor to all three essays in this dissertation. Permissions have been given from the co-authors to include the three essays in this dissertation.

In the first essay,[1] we investigate whether IT capital has a significant contribution to productive capacity and CU, as well as study the long-run determinants of capacity and CU. Productive capacity is a short-run concept whereby we expect the levels of capital to be relatively fixed except for minor adjustments, with the difference between actual output and capacity being a difference in the flow of labor and materials. CU is measured as the ratio of actual output over productive capacity, and is an important measure of economic activity. The choice of how to increase productive capacity and adjust CU is a most critical management decision, and thus is our motivation for this study.

Using a production-function framework, we find that the broad adoption of IT into the pool of capital since the 1980s may have fundamentally changed the constraints on productive capacity, and consequently the determinants of CU. In particular, we first develop a two-state framework that distinguishes two states of production: the actual output state and the capacity state. After that, we derive separate estimation forms for actual output, capacity, and CU based on the Cobb-Douglas production function. We then estimate our model using two cross-sectional time series industry level datasets that cover U.S. manufacturing industries but over different time periods (i.e., from 1987 to 1999, and from 1998 to 2007, respectively). We find that both IT and non-IT capital have significant contributions to capacity, and that IT capital is a much greater long-run constraint on capacity than non-IT capital - increasing IT capital expands capacity more than increasing non-IT capital. We also confirm that both IT and non-IT capital help to reduce the CU rate since the 1990's,

[1]The original paper was titled "The Impact of IT on Productive Capacity" by Dawei Zhang, Xueqi (David) Wei and Barrie R. Nault, which was presented at The 2011 INFORMS Conference on Information Systems and Technology (CIST 2011), Charlotte, NC, November 12-13, 2011.

again with IT capital's impact being greater than that of non-IT capital. Finally, we split our earlier dataset (i.e., 1987-1999) into pre-internet and post-internet periods and find that IT's impact on capacity is not significant in the pre-Internet period, but significant in the post-Internet period.

In the second essay,[2] we study whether IT investment announcements are informative to investors in the financial markets, especially the option market. According to Beaver (1968) and Sun (2003), anything that causes investors to act can be described as information. So, if an IT investment announcement is informative (i.e., has information content), then it should lead to a change in investors assessment of expected future returns, such that there is an altering of the optimal holding of that firms securities in the portfolios of individual investors. Such actions by investors would be reflected in the abnormal trading volume (Beaver 1968), the changes in which can be interpreted as a measure of investors' lack of agreement on their interpretations of the value of these events (Im, Dow and Grover 2001). Furthermore, we propose using the option market as an alternative venue to the stock market to study the informativeness of IT because of its more informative and quantitative nature, and because of its term structure which allows us to separate the short- and long-term beliefs.

By investigating abnormal trading volume and abnormal open interest in the option market around samples of e-commerce announcement days in the 1996-2002 time frame, we find that IT announcements are informationally rich events - they convey information to investors such that they act on the underlying securities. For purpose of comparison, we also calculate abnormal trading volume for the stock market. We discover that the option market is able to capture such informativeness of IT earlier than the stock market, and that the information from IT announcements generate a greater response from option market investors than from stock market investors. Furthermore, IT announcements are found to mainly convey information about expected firm value in the short term. Finally, we

[2] The original paper was titled "Who Reacts to IT Investment Announcements? by Dawei Zhang, Matthew Lyle and Barrie R. Nault, which was presented at The 2012 INFORMS Conference on Information Systems and Technology (CIST 2012), Phoenix, AZ, October 14-17, 2012.

show that good-news IT announcements are more informative than bad-news and no-news announcements in terms triggering more significant trading actions.

The third essay explores the impact of IT investment decisions on firm risk. We adopt implied volatilities (IV) derived from exchange-traded option prices as our risk measure. IV is a new, forward-looking risk measure from the option market which allows us to explore the impact of IT investments on both short-term and long-term firm risk. It represents the market's expectation of the underlying firm's average stock return volatility over the remaining duration of the option contract. Our motivation comes from mixed findings from prior literature. On the one hand, IT greatly contributes to firm performance and profitability, and to reducing risk by enabling firms to better respond to market uncertainties. On the other hand, as argued by Wang and Alam (2007), IT capability is inherently risky as it is subject to implementation challenges, technological complexity, and integration of IT investments with other organizational resources.

Similar to the second essay, we adopt an event study approach and measure the change in firm risk around the IT announcement dates for the full sample as well as for the sub-samples by firm size, by type of e-commerce investments, and by news type. Using a similar dataset of e-commerce announcements from 1996 to 2002 as the second essay, we find that in general IT investment announcements significantly increase both short-term and long-term firm risk. The general result that IT investment announcements increase firm risk is attributable to IT announcements that are made by smaller firms, involve new initiatives, digital goods, as well as B2B applications. Indeed, the only IT investment announcements that result in reduced long-term firm risk are those for tangible goods e-commerce initiatives. Although implied volatility is stock return price neutral, we find those IT announcements that result in reductions in the stock price - bad news - are mostly responsible for increases in firm risk.

The rest of the thesis is organized as follows. Chapter 2 analyzes IT's impact on productive capacity and CU. Chapter 3 examines the nature of IT investment announcements

- whether they are informational events. Chapter 4 presents how IT investment announcements impact firm risk. Chapter 5 concludes the thesis with a brief summary.

Chapter 2

THE IMPACT OF IT ON PRODUCTIVE CAPACITY AND ITS UTILIZATION RATE

2.1 Introduction

The choice of how to increase productive capacity is a most critical management decision. Over the past twenty years, research on Information Technology (IT) productivity has converged to positive and significant contribution from IT to output at all levels. However, there has been no study exploring IT's contribution to output when all firms are producing at their maximum levels. Of course, the data that we observe are how much firms actually used and produced in order to maximize their profits, and have been the focus in prior IT productivity literature. Yet, assuming a world where all firms in an industry or the economy are producing at a sustainable maximum level, which is the capacity concept we introduce later, we believe IT's contribution to capacity would systematically differ from that to actual output because the excess labor needed to produce at capacity would profoundly raise the utilization level of capital. Perhaps more importantly, IT has the potential to increase capacity beyond its impact on actual output, actually decreasing capacity utilization (CU). Alternatively, in producing actual output IT may allow for more efficient utilization of all capital, thus requiring less capital and increasing CU. This leads to our main goal: to conceptually and empirically demonstrate IT's impact on capacity as well as its utilization rate.

Capacity and CU have long been of interest to business and academics. For managers, how to optimally plan a firm's capacity in order to handle demand variations is among their most challenging tasks, as firms need enough capacity to respond to demand fluctuations while trying to avoid the cost of maintaining too much slack capacity. In capital-intensive industries, such capacity expansion decisions can have substantial financial implications. In fact, capacity is often used as a strategic choice of an incumbent firm to pre-empt competition and deter entry (Spence 1977). For researchers, in operations research in particular, capacity has been extensively studied and their focus has been on optimal capacity planning and expansion under demand uncertainty. In addition, CU has been an important economic indicator. It is a key determinant of corporate profitability and a major indicator of macroeconomic performance (Paraskevopoulos and Pitelis 1995). Indeed, CU has been employed in empirical studies in economics to explain inflation, unemployment, investment behavior, productivity measurement and inventory behavior, and is often used as an indicator of the strength of aggregate demand pressure (Schultze, 1963). However, there is little work in the literature that focuses on IT as a determinant of capacity and CU, and this is where we concentrate our contribution. We focus exclusively on the production side of the story. That is, we do not study how firms manage their capacity or CU rate to match market demand; Rather, we explore the determinants of capacity and CU under the production-function framework.

Milgrom and Roberts (1990) suggest that the adoption of IT drives modern manufacturing that emphasizes quality and speedy response to market conditions. Indeed, IT-enabled modern manufacturing technologies such as numerically controlled machines (CNC), flexible manufacturing systems, computer-integrated manufacturing, robotics, programmable controllers, and modular assemblies make it easier to adjust the level and composition of output. CNC in particular provides additional opportunities to increase CU by making manufacturing more flexible such that machines can be used for a variety of operations (Koltai and Stecke, 2008). In addition, advancements in information systems help firms improve their performance. Inter-organizational information systems, Enterprise Resource Planning, E-commerce platforms, and supply chain management systems all help to reduce cost and improve efficiencies. With the maturity of Internet standards such as Transmission Control Protocol/ Internet Protocol (ICP/IP) and eXtensible Makeup Language (XML), these systems become even more helpful by reducing transaction costs and enabling better coordination and business processes (Gong, Nault and Rahman, 2012). Now, recognized as a general purpose technology, IT has shown substantial productivity at all levels of the economy, thus we can reasonably believe that IT also has an significant impact on productive capacity as well as CU.

We aim to answer three research questions. The first is whether IT capital has a significant contribution to productive capacity, and if so, whether it is greater than its contribution to actual output. The second is to determine which long-run inputs, IT or non-IT capital, is a more binding constraint on productive capacity – that is, which has the greater impact if expanded. The third, and most critical, is whether increases in IT capital lead to lower CU due to IT's greater relative impact on capacity or whether such increases lead to higher CU due to IT's impact on production efficiency. We explore these questions by first introducing the definition of capacity and CU that we adopt. Then, we develop a two-state framework that distinguishes two states of production: the actual output state and the capacity state. After that, we derive separate estimation forms for actual output, capacity, and CU based on the Cobb-Douglas production function. Next, we estimate our models using two cross-sectional time series industry-level datasets that cover mainly U.S. manufacturing industries but different time periods. We find that both IT and non-IT capital have significant contributions to capacity, and that IT capital is a much greater constraint on capacity than non-IT capital. We also confirm that both IT and non-IT capital helps to reduce the CU rate since the 1990's. Finally, we split our earlier dataset into pre-internet and post-internet periods and find that IT's impact on capacity is not significant in the pre-Internet period, but significant in the post-Internet period.

The remainder of the paper proceeds as follows. For the rest of this section we introduce our adopted definition of capacity and CU, and review related literature. Next, we develop a two-state framework that distinguishes capacity from actual output. Following that, we develop mathematical estimation models for output, capacity, and CU respectively, estimate the models and present our findings. The last section discusses our findings and contributions.

2.1.1 Background Literature

Overview of Capacity and Capacity Utilization Although the word "capacity" can have different meanings in different contexts, we study "productive capacity" which is often referred to the maximum possible output of a production unit. Specifically, we adopt the definitions of capacity and capacity utilization (CU) from the Federal Reserve Board (FRB), which defines capacity as the *"sustainable maximum output - the greatest level of output a plant can maintain within the framework of a realistic work schedule, after factoring in normal downtime and assuming sufficient availability of inputs to operate the capital in place"* (Corrado, Gilbert, and Raddock 1997).

With this definition, CU can be understood as a ratio of the actual level of output to a sustainable maximum level of output, or capacity. Importantly, capacity is inherently a short-run concept, constrained by capital in place and achieved by adding variable inputs to the limit of what the capital in place can accommodate. As indicated by Morrison (1985), the FRB calculation of capacity and CU is *"based more on data analysis - both statistical and judgmental - than on economic theory (p. 313)"*. Although we recognize there is an economic measure of capacity that is related to optimal levels of production (Cassells 1937, Friedman 1963, Berndt and Morrison 1981, Morrison 1985, Fousekis and Stefanou 1996), we focus on a physical (technological) measure of capacity and CU.

Capacity and CU have been used in economics to explain inflation, capital investment and labor productivity (Greenwood, Hercowitz and Huffman 1988, Shapiro, Gordon and Summers 1989, Gordon 1989, 1998, Dexter, Levi and Nault 2005, etc.). Because of their strong predictive value for these macroeconomic variables, economists have been developing better measures of capacity and CU (Cassells 1937, Hickman 1964, Chenery 1952, Klein 1960, Friedman 1963, Berndt and Morrison 1981, Morrison 1985, Berndt and Fuss 1989, Fousekis and Stefanou 1996, Sahoo and Tone 2009). These measures have been empirically implemented to assess the tightness of the economy in broad industrial environments including manufacturing (Berndt and Morrison, 1981), the automobile industry (Morrison, 1985), privately owned electric utilities (Nelson, 1989), the food processing and distribution sector (Fousekis and Stefanou, 1996), fishing industries (Kirkley and Squires, 1999), and in the manufacturing sectors of nine OECD countries (Berndt and Hesse, 1986). Our focus is not the measurement of capacity or CU, but rather the determinants of the short-run productive capacity at the industry level. To the best of our knowledge, there has not been any work that considers a similar problem.

There has been extensive literature in operations on the determinants of capacity. In particular there has been a focus on capacity expansion or optimal capacity, under the common assumption that capacity decisions often need to be made in the presence of high demand uncertainty (see Luss (1982), Cakanyildirim and Roundy (1999) for a detailed survey on capacity expansion models and Zhang, Roundy, Cakanyildirim, and Huh (2004) on capacity planning). Capacity has also been identified and modeled as a strategic decision to deter entry (Spence 1977), and has been shown to be affected by price postponement (Biller, Muriel and Zhang 2006), financing restrictions (Lederer and Singhal 1994, and Boyabatli and Toktay 2011), information asymmetry (Wang and Barron 1995), etc. Rather than market demand influences, our work focuses on the impact of quasi-fixed (i.e., unchangeable in the short-run) input-constraints on capacity.

There has also been extensive research on the determinants of CU. Banker, Conrad and Strauss (1986) find CU to be closely related to the Data Envelopment Analysis measure of technical efficiency which reflects the radial distance from the directly estimated production frontier. Lecraw (1978) finds that the firm-level CU rate is a function of the nationality of the firm's owner, entry date, number of firms in the industry, projected profits, and the manager's perceived risk of multi-shift operations. By examining Korean Manufacturing data, Lee and Kwon (1994) find wages and material prices have positive effects on CU, while energy prices and capital stock having negative effects. They also find that overambitious government incentive policies to stimulate investment may have an adverse effect on CU. Making use of data from 40 chemical product industries over roughly two decades, Lieberman (1989) finds that CU was positively related to capital intensity and the trend rate of demand growth, and was negatively related to demand variability, geographic plant dispersion, and plant "lumpiness". Gajanan and Gajanan (2009) study the determinants of Indian manufacturing industries and find that CU is positively related to the magnitude of labor intensity in production.

IT and Productivity   Our work lies in the framework of IT productivity as we study IT's productivity for a special level of output - the sustainable maximum output. There has been extensive empirical research about the impact of IT on output. In that research, it is usually assumed that IT is both similar and different from other inputs in the way IT enables production and interacts with other inputs. Since the late 1990's, research evaluating the contribution of IT investments under the production function framework has converged on a positive IT contribution (Cheng and Nault 2007). Using data from Computerworld and InformationWeek, Lichtenberg (1995) indicates that returns yielded by IT investment are significantly greater than those earned by other factors. Employing the International Data Group annual survey data for information systems spending by 367 large U.S. firms, Brynjolfsson and Hitt (1996) found IS spending has made a significant contribution to firm output. Using the same dataset, Dewan and Min (1997) show that "*IT capital is a net substitute for both ordinary capital and labor, suggesting that the factor share of IT in production will grow to more significant levels over time* (p. 1660)". Chwelos, Ramirez, Kraemer and Melville (2011) find that more recently IT capital and non-IT capital are complements.

Besides the direct impact of IT on productivity, there are many other ways that IT affects productivity. Brynjolfsson and Hitt (2000) argue that investment in IT enables complementary organizational investments such as business processes and work practices leading to cost reductions and quality improvements. Bresnahan, Brynjolfsson and Hitt (2002) show that higher levels of IT are associated with increased delegation of powers to teams and individuals, and greater levels of skills and education of the workforce. Autor, Levy and Murnane (2003) suggest that the adoption of IT has substituted for routine labor tasks and complemented non-routine cognitive tasks, especially in rapidly computerizing industries. Apart from the direct business value IT generates, Mittal and Nault (2009) find evidence that indirect effects of IT are also significant as IT augments other factor inputs such as non-IT capital and labor. IT from adjacent industries demonstrates significant spillover effects as IT investment made upstream (downstream) significantly impacts productivity downstream (upstream) (Cheng and Nault 2007, 2011).

IT, Capacity, and CU Although there has been extensive literature on the measurement and general determinants of capacity and CU and on IT productivity, there has been little work on the relationship between IT and capacity and CU. Furthermore, the limited empirical findings on this relationship have been mixed.

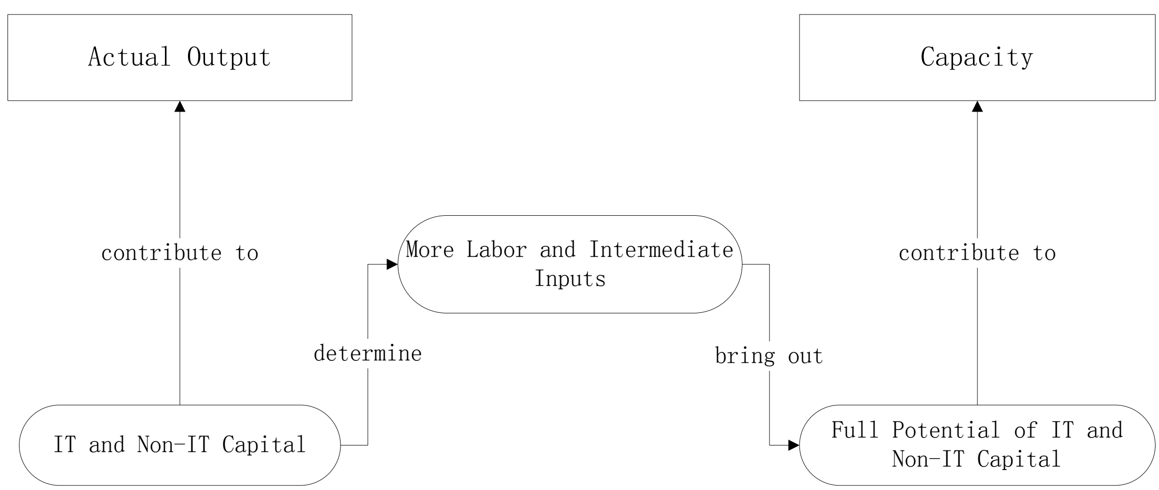
Barua, Kriebel and Mukhopadhyay (1995) find that IT explained improvements in the intermediate process-level measures such as CU and inventory turnover. Through case studies in elevators, retailing, telecommunications and investment banking, Nightingale, Brady, Davies and Hall (2003) show that the adoption of IT-intensive capital-based control systems can significantly improve the allocation of system traffic, which in turn, can increase CU and enhance system performance. However, using panel data on 111 manufacturing industries, Bansak, Morin and Starr (2007) empirically estimates the impact of high-tech capital on CU and show that increased use of technology is associated with a reduction in CU, controlling for output growth, investment, and other factors. They also suggest two directions in which recent technological changes may have an impact on CU. On the one hand, new technologies may make it easier to ramp production up and down. Combined with falling prices of high-tech equipment, this may encourage firms to install a broader margin of excess capacity - operating at lower average utilization - to be able to handle upswings in demand. On the other hand, because automated design and modular units make capacity expansion faster and cheaper, firms may prefer to operate at higher average utilization, expecting to be able to boost capacity should demand turn out to be strong. This question - whether IT increases or decreases CU, is one of the primary research questions we answer in our results.

2.2 Our Framework and Model

2.2.1 A Two-State Framework

We propose a two-state framework below for actual output and productive capacity (Figure 2.1), and illustrate it using an industry example.

Figure 2.1: **A Two-State Framework for Actual Output and Capacity**



Because we study IT's productivity in terms of contribution to sustainable maximum output, or capacity, and to be consistent with prior research on IT productivity, we develop a two-state framework using production theory, where a combination of inputs (eg. labor, capital, intermediate inputs, etc) are transformed into a final product by a production process which is usually represented by a production function. The two square boxes in Figure 1 represent two states of production: the actual output state and the capacity state. In the actual output state, firms produce at a level of output to maximize their profits. In the capacity state, however, firms produce at capacity by increasing labor and intermediate inputs to a sustainable limit. There is no sequential relationship between the two states. That is, firms do not need to go through the actual output state first in order to reach the capacity state. In fact, as most of the time it is not optimal for firms to produce at capacity because of insufficient demand, actual output is almost always strictly less than capacity, which makes the capacity state a conceptual state.

IT productivity research has predominantly focused on IT's impact on actual output, that is, in the actual output state. However, the actual output and capacity states are distinct in the way inputs are managed and utilized for production, thus they represent two different production processes in terms of the productivity of the inputs. Therefore, we expect that the output elasticities of inputs and total factor productivity (TFP) all differ when all the firms are producing at the conceptual "sustainable maximum output" level, or the capacity state as compared to the actual output state. We focus on the effects of the two quasi-fixed variables, IT and non-IT capital, in the capacity state.

We illustrate our two-state framework with an example adapted from part of the Harvard Business Case "Capacity Analysis: Sample Problems" (9-696-058). Consider a molding factory that produces an automobile component. There are eleven in-house molding machines, which are software-controlled and equipped with advanced technologies. Each machine requires a full-time operator whose job includes loading, unloading, actively monitoring, and making necessary adjustments to the machines. One of the eleven machines is always being maintained or repaired at any given time. There are normally only six operators dedicated to molding. The molded parts are then assembled with other parts, which are freely available, by fifteen workers working an eight-hour shift on an assembly line to make the final components. The speed of the assembly line is controlled by software and can be increased or decreased according to labor availability. In order to produce at its capacity level during a single shift, the factory would need at least an additional four operators. Overall, the factory can hire fourteen more operators in order to have two shifts a day, each with ten machines running full-time. In order to assemble these molded parts, the assembly line needs to be running at its fastest speed that requires twenty workers at the same time. Therefore, the factory would need at least another five workers on the assembly line during a single shift, and may hire another twenty for a second shift. During this short-run boost from actual output production to capacity, the total amount of IT and non-IT capital stock remain fixed. However, the labor input, and its scheduling and management all deviate from before, which raises the utilization rate of capital in place and therefore alters the returns to each input during the production process.

IT and non-IT capital constrain the production increase from the actual output state to the capacity state that is accompanied by the expansion of labor and intermediate inputs. First, the maximum amount of productive labor and intermediate inputs that can be used for production are determined by the amount/level of IT and non-IT capital in place. Referring back to our molding factory example, additional labor can be used only to the degree that there are more machines in place. Furthermore, if the machines are not digitally controlled and installed with less advanced technology, each of them may require two full-time operators at the same time, which doubles the additional labor required but does not necessarily increase the capacity. Therefore, IT and non-IT capital constrains the sustainable maximum output by bounding the maximum amount of usable labor input. Second, IT has significant indirect effects through labor and non-IT capital (Mittal and Nault 2009). Therefore, IT contributes to capacity by making non-IT capital and the expanded labor input more productive. Third, utilizing maximal labor input helps to bring out the full potential of firms'

IT and non-IT capital stock. Using our example again, the utilization rate of the machines (including both IT and non-IT capital) is raised substantially when there are more operators available. Also, the sufficient supply of workers guarantees that the assembly line can run at full speed. Hence, we expect the contributions of IT and non-IT capital in the capacity state to be greater than those in the actual output state. Moreover, we expect the relative magnitude of the contributions between the two types of capital to be different. On the one hand, the same level of IT and non-IT capital are used to produce more output in the capacity state than in the actual output state; on the other hand, there are also more labor and intermediate inputs in the capacity state. Therefore, it is not clear if IT and non-IT capital have greater impacts on output in the capacity state than in the actual output state, or if the newly-added labor and intermediate inputs account for this boost in production. Our estimation models in the next section answer this question.

As IT affects both actual output and capacity, naturally it also impacts CU because CU is a ratio of actual output over capacity. The overall influence of IT on CU depends on the relative marginal change it brings to actual output and capacity. In other words, if IT's relative contribution to capacity is greater than to actual output, CU will be lower with more IT; otherwise CU will be higher with more IT. We develop a separate estimation form for CU in the next section.

2.2.2 Estimation model

Productive capacity and CU are inherently short-run concepts, conditional on the firm's stock of quasi-fixed inputs, that is, inputs that are not adjustable in the short run. We consider a firm that produces only one output with two variable inputs and two quasi-fixed inputs. In order to be comparable and compatible with the bulk of research on the productivity of IT, our production function for actual output is based on a Cobb-Douglas (CD) form,

$$Y = AL^{\alpha}K^{\beta}Z^{\gamma}M^{\theta}, \tag{2.1}$$

where Y is actual output measured in real dollars, L is labor hours or full-time equivalents, K is the stock of non-IT capital measured in real dollars, Z is the stock of IT capital measured in real dollars, and M is intermediate inputs also measured in real dollars. The CD form represents production for a defined period of time, for example a year. Output, labor and intermediate inputs are flows, and the two capitals are stocks. In some formulations the capital stocks are converted to flows by the rental price method, although there is generally little effect on the estimates. A is the technical change parameter, usually representing Total Factor Productivity (TFP). The parameters α, β, γ and θ are the output elasticities of labor, non-IT capital, IT capital, and intermediate inputs respectively. The output elasticities represent the percentage increase in output from a marginal percentage increase in the input. Using lower-case letters to represent the (natural) logs of the corresponding upper-case letters, the CD production function in log form is

$$y \;=\; a \;+\; \alpha l \;+\; \beta k \;+\; \gamma z +\; \theta m. \tag{2.2}$$

Notice that the variables in (2.1) and (2.2) are the actual values of inputs that were used by industries and the actual values of output that were produced, which correspond to the actual output state in our two-state framework since actual production is rarely at the capacity state. To model the relationship between inputs and capacity (rather than actual output) in the capacity state, we take IT and non-IT capital as quasi-fixed, and labor and intermediate inputs as variable inputs that are available in sufficient quantities and at current market prices as to achieve maximum sustainable output. These definitions are consistent with the measures obtained from the FRB, which we discuss in more detail in the data description below.

With our measure of capacity, which we write as Y_c, or y_c in log form, and using a CD-based production function form, we represent capacity production as

$$Y_c \;=\; A_c L_c^{\alpha_c} K^{\beta_c} Z^{\gamma_c} M_c^{\theta_c}, \tag{2.3}$$

and in log form

$$y_c = a_c + \alpha_c l_c + \beta_c k + \gamma_c z + \theta_c m_c. \tag{2.4}$$

In (2.3) and (2.4) we use the subscript c to denote terms in the capacity model. As we discussed in our two-state framework, producing at capacity follows a systematically different production process than producing at actual output in terms of productivity of the inputs. Labor and intermediate inputs as variable inputs are marked with the subscript c to indicate their levels when producing at capacity, and the two types of capital – the quasi-fixed inputs, are kept at the same levels as they are when producing at the level of actual output. Thus, the equation in (2.4) captures the relationship between the inputs, some variable and some fixed, required to produce a level of output consistent with maximum sustainable output. In other words, given fixed IT capital and non-IT capital, (2.4) embodies the increased levels of labor and intermediate inputs needed to produce at capacity.

Our interest is focused on the two output elasticities of capital, β_c and γ_c, and their corresponding marginal products, because these values effectively capture the degree to which each type of capital constrains capacity. Specifically, the output elasticities represent the effects of the inputs on capacity in terms of percentages, whereas the marginal products demonstrate such effects in terms of actual dollar returns. As a 1% change in different inputs means different amounts of dollars, the output elasticity is not sufficient to compare the effects of inputs on capacity in terms of actual dollar returns. Instead, we compare the marginal products to conclude which type of capital is a more binding constraint on capacity. In other words, if the marginal product of IT (non-IT) capital is greater than that of non-IT (IT) capital, then increasing IT (non-IT) capital is more important for increasing capacity. Because capacity is defined as maximum sustainable output, (2.3) and (2.4) are essentially results of a constrained optimization where the amounts of non-IT capital and IT capital are the constraints. Therefore, another way to understand the output elasticities (marginal products) of the two capitals is pseudo-shadow prices: they represent the marginal return in percentage (actual dollars) to capacity by relaxing the constraint of keeping capital fixed from (2.2) to (2.4) by one percent (one dollar).

The values of capacity, non-IT capital and IT capital are available for (2.4) through capacity-type measures and production data. Unfortunately, there is no such source for labor and intermediate inputs in (2.4) as these are figures which are conceptual - they are quantities that must be scaled up to produce at capacity. There is also no source to derive the scaling because production functions represent an optimal input mix. Although we can derive marginal products of labor and intermediate inputs or simply scale them up proportionally from the level for actual output to that for capacity, these marginal products or proportional scaling are unlikely to hold through an expansion from actual output to capacity, and especially so given capital is fixed. A good example is a pulp and paper plant: the plant may require five operators to run at any level of output, so that increased labor is not required to increase to capacity. Our molding factory example in the previous section also shows the difficulty of using current level of marginal product to calculate the extra labor needed in order to produce at capacity. Because the machine operators and assembly line workers have different contributions to production, the marginal product of labor for actual output in the factory is an overall measure of contribution of these two types of labor. During the expansion from actual output to capacity, however, the need for more of these two types of labor are likely distinct from each other. Therefore, only in special circumstances would the labor input demonstrate constant returns to scale or some other easily identifiable scaling moving from actual output production to capacity. Moreover, from an econometric perspective, scaling up labor and intermediate inputs using marginal products or proportional scaling would involve capacity, which is the dependent variable in (2.4), causing an obvious reverse-causality problem for the estimation.

Recognizing that the scaling of labor and intermediate inputs is likely industry-specific or even firm/plant-specific, we resolve this problem by allowing the data to scale up labor and intermediate inputs. Using industry-level data, we can allow any industry to be the base industry, and estimate a variant of (2.4),

$$y_c \;=\; a_c \;+\; \delta_{c,0} l + \sum_{i \neq 0} \delta_{c,i} d_i l \;+\; \beta_c k \;+\; \gamma_c z + \;\eta_{c,0} m + \sum_{i \neq 0} \eta_{c,i} d_i m, \tag{2.5}$$

where the summation is over the total number of industries minus one, d_i is an industry dummy variable with i representing a specific industry, and $\delta_{c,j}$ and $\eta_{c,j}$ ($j \in \{0, i\}$) are to be estimated. Here $\delta_{c,0}$ and $\eta_{c,0}$ capture the scaled output elasticities of the variable inputs for the base industry, and $\delta_{c,i}$ and $\eta_{c,i}$ capture the scaling of output elasticities of the variable inputs for industry i ($i \neq 0$). Putting together, we use $\delta_{c,0} l + \sum_{i \neq 0} \delta_{c,i} d_i l$ as an approximation for the product of scaled labor and its output elasticity, which is $\alpha_c l_c$ in (2.4). We do the same for intermediate inputs (m). It is worth recognizing that the values of $\delta_{c,j}$ and $\eta_{c,j}$ ($j \in \{0, i\}$) in (2.5) are not of particular interest, and simply serve to scale up the variable inputs to arrive at estimates of the two output elasticities of capital, β_c and γ_c.

Given (2.1) and (2.3), we are able to develop a reduced estimation form for CU starting from

$$CU \;=\; \frac{Y}{Y_c} \;=\; \frac{A}{A_c} \frac{L^{\alpha}}{L_c^{\alpha_c}} K^{\beta - \beta_c} Z^{\gamma - \gamma_c} \frac{M^{\theta}}{M_c^{\theta_c}},$$

where CU is defined as a ratio of actual output over capacity, each represented by a Cobb-Douglas production function. To linearize the form, we take its log

$$logCU \;=\; (a \;-\; a_c) \;+\; \alpha l \;-\; \alpha_c l_c \;+\; (\beta - \beta_c) k \;+\; (\gamma - \gamma_c) z \;+\; \theta m \;-\; \theta_c m_c,$$

where l_c and m_c are again conceptual and thus not directly observable. We apply the same scaling method as in (2.5) to replace l_c and m_c and obtain our estimation form for CU that combines our output and capacity equations

$$logCU \;=\; a_u \;+\; \delta_{u,0} l \;+\; \sum_{i \neq 0} \delta_{u,i} d_i l \;+\; \beta_u k \;+\; \gamma_u z + \;\eta_{u,0} m + \sum_{i \neq 0} \eta_{u,i} d_i m, \tag{2.6}$$

where $a_u = a - a_c$, $\beta_u = \beta - \beta_c$, and $\gamma_u = \gamma - \gamma_c$. The subscript u on the coefficients represent that they come from the CU equation, (2.6). Similar to (2.5), $\delta_{u,0}$ and $\eta_{u,0}$ represent the scaled effects of the variable inputs on $logCU$ for the base industry, and $\delta_{u,i}$ and $\eta_{u,i}$ capture the scaling of such effects for industry i ($i \neq 0$) in this particular equation. Again, as in (2.5), we are only interested in β_u and γ_u, which measure the elasticities of non-IT and IT capital on CU. Specifically, if the sign is negative, it means its corresponding capital helps to reduce CU by creating more capacity relative to actual output; if positive, then the effect is reversed leaving less slack capacity (eg. increasing the corresponding capital generates more actual output relative to capacity). Although we can separately estimate β (γ) from (2.2) and β^c (γ^c) from (2.5), (2.6) allows us to estimate their difference as one term and test if it is statistically different from zero.

2.2.3 Data Description

We have two cross-section time-series datasets, each covering different time periods and industries at different aggregation levels. Summary statistics for Dataset I and II are provided in Figure 2.2 below. A detailed description of the industries in each dataset is provided in Figure 5.1 and Figure 5.2 in the Appendix.

Dataset I: 1987-1999 The first dataset is the result of matching a productivity dataset with a CU dataset, both from 1987 to 1999. The productivity dataset is the same as the one used in Cheng and Nault (2007). It is collected from the Bureau of Labor Statistics (BLS), and covers 140 three-digit Standard Industrial Classification (SIC) code manufacturing industries. The productivity dataset contains labor input (L), IT capital stock (Z), non-IT capital stock (K), and gross output (Y). The last three variables are converted to millions of 1987 dollars, by dividing their nominal values in millions by their corresponding deflators. The labor input is in millions of hours. The IT capital stock was requested from BLS, and is an aggregation of the stock of computers and related equipment, office equipment, communication, instruments, photocopy and related equipment. From a breakdown of asset types, the non-IT capital stock is computed as the total of equipment and structures less IT

Figure 2.2: **Summary Statistics**

Variable	Mean	Std. Dev.	Min	Max
Dataset I (1987-1999)				
Output (in millions of 1987 dollars)	63714.56	75386.87	2926.97	738130.80
Intermediate inputs (in millions of 1987 dollars)	36670.75	43113.01	1425.65	245896.60
Labor (in millions hours)	913.60	899.73	27.10	3599.50
Non-IT capital stock (in millions of 1987 dollars)	43662.16	42219.60	3877.70	202606.40
IT capital stock (in millions of 1987 dollars)	3979.03	5086.10	82.60	29408.60
Capacity utilization (in percentage*100)	83.28	7.00	55.34	98.98
Capacity (in millions of 1987 dollars)	77834.01	92029.29	3078.72	885654.20
Dataset II (1998-2007)				
Output (in millions of 2000 dollars)	203951.00	174105.30	19187.03	672739.00
Intermediate inputs (in millions of 2000 dollars)	128460.60	118099.30	10193.24	490605.00
Labor (in millions hours)	1536.65	1051.74	231.00	4329.00
Non-IT capital stock (in millions of 2000 dollars)	142041.80	136898.20	17683.00	716012.00
IT capital stock (in millions of 2000 dollars)	13387.47	15426.98	898.00	63689.00
Capacity utilization (percentage*100)	79.13	6.36	60.36	94.46
Capacity (in millions of 2000 dollars)	262018.90	231967.50	25645.37	918285.00

Notes. Dataset I has 507 observations; Dataset II has 210 observations.

capital stock.

In order to match with the SIC-based productivity dataset, we requested SIC-based CU data from the FRB. It covers 45 SIC code manufacturing industries at the two-digit or three-digit level from 1987 to 1999. The FRB estimates of CU are developed from a combination of sources - about 22 percent of total industrial capacity data are from government sources and trade sources, about 73 percent of total industry capacity data are based on responses to the Bureau of the Census's Survey of Plant Capacity and roughly 5 percent of total industry capacity data are based on trends through peaks in production. We collect CU data from FRB because this data source has been the most consistent over time, that is, a CU rate of 85 percent today means about the same degree of tightness in production that it meant in the past. Moreover, it covers a broad span of industries and sufficiently long time periods.

For each industry in a certain year, the CU index is essentially the ratio of nominal output divided by nominal capacity for a given industry-year. We cannot directly use the capacity index data from FRB since they are not comparable between industries. We thus calculate our capacity measure (Y_c) by dividing the gross output variable (Y) in the productivity dataset by CU. Since Y is already in millions of 1987 dollars, Y_c is also in millions of 1987 dollars. As the SIC capacity dataset contains industries at both two-digit and three-digit levels, we aggregate the productivity dataset to match the industries in the capacity dataset. The result is a balanced panel of 39 industries across 13 years. Figure 5.1 in the Appendix lists the 39 manufacturing industries and their SIC codes.

To control for sector-level heterogeneity, we generated sector dummy variables following Stiroh (2002) and Cheng and Nault (2011): IT-producing industries are the industries with the first two digits of SIC code being 35 (Industrial Machinery and Equipment) or 36 (Electronic and other Electric Equipment); IT-using industries are the industries which are not IT-producing and whose IT intensity (IT capital stock over gross output) is above the sample median of the non-IT producing industries; the remaining industries are classified as others. This yields 5 IT-producing, 16 IT-using, and 18 other industries.

Dataset II: 1998-2007 The second dataset is more recent and based on the 2002 North American Industry Classification System (NAICS). We acquired data on capital stock, IT capital stock, and labor input for 59 three-digit NAICS code industries from 1998 to 2007, directly from the BLS website. There are four categories for IT capital stock: computers, software, communication, and other. The productive capital stock of these four categories are aggregated as IT capital stock (Z). For the non-IT capital stock (K), similar to the first dataset, we totaled the equipment and structure components of the asset types and subtracted the IT capital stock from it. Both IT capital and non-IT capital are collected in millions of 2000 dollars, as is intermediate inputs, M. The labor input, L, is in millions of hours as in the first dataset. We also collect GDP at the three- digit NAICS code level from the Bureau of Economic Analysis (BEA), and deflate it by the corresponding chain-type quantity indexes for output, which yields the real gross output Y in millions of 2000 dollars.

We then collect 2002 NAICS-based CU data from the FRB website. The data are at a mix of different digit levels. The definition of CU is the same as in Dataset I. This NAICS-based CU dataset covers 89 detailed industries (71 in manufacturing, 16 in mining, and 2 in utilities). Because the CU data are aggregated from the establishment level for each industry, they are not additive across industries. Therefore, we aggregate the productivity dataset according to the levels of industries in the CU dataset, and then match the two datasets. The result is a balanced panel of 21 industries (18 in manufacturing and 3 in mining) across 10 years. We then generate capacity, Y_c, as in Dataset I. For Dataset II we classify the industries into two sectors: manufacturing (NAICS codes 31-33) and non-manufacturing, and create a dummy variable for the non-manufacturing sector. This sector dummy helps to control for any sector-level, time-invariant factors that may contribute to industry output. Figure 5.2 lists the 21 industries and their NAICS codes.

2.2.4 Econometric Adjustments

Heteroscedasticity and autocorrelation are the two econometric problems that commonly arise when using cross-sectional time series data. Our industries differ in size, organization, management, production technology, and response to economic shocks. Thus, we expect our datasets to exhibit heteroscedasticity between industries, and possibly correlated across industries. We also expect our datasets to exhibit first-order autocorrelation because with relatively smooth business cycles one year's output is highly correlated with the prior year's output. Moreover, if the responses to changes in business cycles do not occur with the same magnitude in each industry, then each industry may differ in its magnitude of autocorrelation and the autocorrelation becomes industry-specific.

Using the Wooldridge test for autocorrelation in a panel dataset, we rejected the null hypothesis of no first-order autocorrelation (AR1) at reasonable levels of significance in both datasets for the model of actual output (equation (2.2), F-statistic=10.97 for Dataset I and 50.82 for Dataset II, both reject at the 1% level), for the model of capacity (equation (2.5), F-statistic=27.080 for Dataset I and 8.024 for Dataset II, reject at the 1% and 5% level respectively), and for the model of CU (equation (2.6), F-statistic=76.251 for Dataset I and 8.983 for Dataset II, both reject at the 1% level). Furthermore, we adopt the likelihood ratio test to test if the autocorrelation is panel-specific (PSAR1). We are able to reject the null hypothesis that the AR1 coefficients are common across panels for the model of output (χ^2 = 217.86 for Dataset I and 49.35 for Dataset II, both reject at the 1% level), for the model of capacity (χ^2 = 57.73 for Dataset I and 70.65 for Dataset II, reject at the 5% and 1% level respectively), and for the model of CU (χ^2 = 60.68 for Dataset I and 43.18 for Dataset II, reject at 5% and 1% level respectively). Finally, we use the likelihood ratio test to check for the presence of panel-level heteroscedasticity (He), and find that the null hypothesis of no panel-level heteroscedasticity is rejected at the 1% level for the model of actual output (χ^2 = 771.09 for Dataset I and 238.36 for Dataset II), for the model of capacity (χ^2 = 536.46 for Dataset I and 202.60 for Dataset II), and for the model of CU (χ^2 = 297.52 for Dataset I and 104.35 for Dataset II).

Given our test results, we have evidence that both panel-specific autocorrelation and panel-level heteroscedasticity are present in both of our datasets. To adjust for these econometrically, we estimate our models using specifications for heteroscedastic errors and industry-specific AR1 coefficients (He + PSAR1). To generate our estimates, we use cross-sectional time series feasible generalized least-squares (FGLS) regressions (Wooldridge 2002) implemented in Stata. Furthermore, we add year dummies to control for the potential economy-wide shocks. Rather than using fixed effects, we control for the industry-specific heterogeneity in a general manner by including the sector dummies (i.e., IT-producing and IT-using for Dataset I, and non-manufacturing for Dataset II) and allowing for industry-specific autocorrelation. We note that historically, fixed-effects estimation has led to disappointing results with insignificant capital coefficients and implausibly low returns to scale (Griliches and Mairesse 1998, Stiroh 2010, Cheng and Nault 2011). We also do not include controls for correlated industry-level heteroscedasticity as the number of industries is greater than the number of years in both of our datasets.

2.3 Results

2.3.1 Baseline Results

Our baseline results for the two datasets are reported in Figure 2.3 (output elasticities) and Figure 2.4 (marginal products). For each dataset there are three sets of results corresponding to the actual output model in (2.2), the capacity model in (2.5), and the CU model in (2.6), respectively. The actual output results are included for comparison and a better understanding of our capacity and CU results. Recall that our interests are the impacts of IT capital and non-IT capital, which are our primary focus throughout the results section.

Figure 2.3: **Main Results - Output Elasticities**

	1987-1999			1998-2007		
	Actual Ouput	Productive Capacity	CU	Actual Ouput	Productive Capacity	CU
IT Capital	0.077 ***	0.133 ***	0.036	0.032 *	0.137 ***	-0.183 ***
	(0.019)	(0.024)	(0.022)	(0.018)	(0.049)	(0.048)
Non-IT Capital	0.101 ***	0.437 ***	-0.634 ***	0.289 ***	0.728 ***	-0.305 **
	(0.02)	(0.061)	(0.055)	(0.031)	(0.148)	(0.145)
Labor	0.264 ***			0.116 ***		
	(0.018)			(0.021)		
Intermediate Inputs	0.571 ***			0.558 ***		
	(0.024)			(0.023)		
Returns to Scale	1.013			0.995		
N	507	507	507	210	210	210

Notes. Log dependent variable and input variables. Feasible Least Squares estimation. IT-producing, IT-using, and the year dummies are included for the 1987 -1999 dataset. Non-manufacturing and the year dummies are included for the 1998 -2007 dataset. Dummies and interaction terms are suppressed for brivety. Control for panel-specific heteroskedasticity (PSHe) and panel-specific autocorrelation (PSAR1) for both datasets
∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

Figure 2.4: **Main Results - Marginal Products**

	1987-1999						1998-2007					
	Actual Ouput †		Capacity †		CU ‡		Actual Ouput †		Capacity †		CU ‡	
IT Capital	2.520	***	5.224	***	4.788		0.731	*	3.987	***	-3.111	***
	(0.622)		(0.943)		(2.926)		(0.411)		(1.426)		(0.816)	
Non-IT Capital	0.155	***	0.819	***	-3.000	***	0.506	***	1.639	***	-0.305	**
	(0.031)		(0.114)		(0.260)		(0.054)		(0.333)		(0.145)	
N	507		507		507		210		210		210	

† Marginal products

‡ Marginal impact on industry-average CU per one billion dollar increase

*p<0.10, **p<0.05, ***p<0.01. Standard errors in parentheses.

Results on Actual Output   Because of the aggregation necessary to match the productivity data with the capacity data, we first examine estimates from the Cobb-Douglas form, and ensure they are comparable with prior IT productivity results that have used this form. Our estimates from the simple Cobb-Douglas regression on actual output in (2.2) are reported in Column 2 for Dataset I and Column 5 for Dataset II in Figure 2.3 (output elasticities) and Figure 2.4 (marginal products). Our output elasticities of IT capital for the 1998-2007 dataset is comparable in magnitude with previous findings, however only significant at the 10% level. The rest of our output elasticities, as well as our marginal products across the two datasets are all significant at the 1% level and conform in magnitude to the previous findings (See Table 4 in Cheng and Nault 2007) even though the prior studies differ in data sources, aggregation, and econometric adjustments. Moveover, consistent with prior research, our measures of the returns to scale in Figure 2.3 are close to one, indicating constant returns to scale in both datasets.

Results on Productive Capacity   The estimates from our model on capacity in (2.5) are presented in Column 3 for Dataset I and Column 6 for Dataset II in both Figure 2.3 (output elasticities) and Figure 2.4 (marginal products). The output elasticities of IT and non-IT capital, β^c and γ^c in (2.5), are positive and significant at the 1% level in both datasets, which answers our first research question. In particular, the output elasticity of non-IT capital ($\beta^c = 0.437$ in Dataset I and 0.728 in Dataset II) is much greater in magnitude than that of IT-capital ($\gamma^c = 0.133$ in Dataset I and 0.137 in Dataset II) in both datasets, indicating that on average, a 1% increase in non-IT capital is associated with a much larger percentage change in an industry's productive capacity than that of IT-capital. However, when we convert the elasticities to marginal products (MP), the MP for IT is much greater than that for non-IT capital (MP for IT =5.224 in Dataset I and 3.987 in Dataset II; MP for non-IT =0.819 in Dataset I and 1.639 in Dataset II). This indicates that a one dollar investment in IT capital has a higher return to capacity compared to that in non-IT capital. As both types of capital are fixed in the short-run, they become the constraints on capacity. Thus, an alternative way to understand this result is to think of the MPs as the shadow prices for capacity. In other words, MPs represent the dollar gains in capacity by relaxing the capital constraint by one dollar. With this interpretation, our results show that relaxing the IT capital constraint yields a greater payoff on capacity than non-IT capital, which answers our second research question.

The output elasticities of IT and non-IT capital for capacity in (2.5) are both greater in magnitude than their corresponding estimates for actual output in (2.2), indicating that despite the increase in labor and intermediate inputs, both IT and non-IT capital contribute to the output boost from actual output to capacity. Moreover, comparing the output elasticities of IT and non-IT capital between the actual output model and the capacity model, non-IT capital has a much greater rise in magnitude than IT capital from the output model to the capacity model in both datasets ($\beta^c - \beta = 0.336$ in Dataset I and 0.438 in Dataset II; whereas $\gamma^c - \gamma = 0.056$ in Dataset I and 0.105 in Dataset II). In addition, the difference in magnitude between the output elasticity of IT capital and that of non-IT capital increases in the capacity model ($\beta - \gamma = 0.024$ ($\chi^2 = 0.51$, $p - value = 0.48$) in Dataset I and 0.257 ($\chi^2 = 33.49$, $p - value = 33.49$) in Dataset II; whereas $\beta^c - \gamma^c = 0.304$ ($\chi^2 = 16.40$, $p - value = 0.00$) in Dataset I and 0.591 ($\chi^2 = 10.22$, $p - value = 0.00$) in Dataset II). Similarly, the MPs of IT and non-IT capital for capacity in (2.5) are both greater in magnitude than those for actual output in (2.2), and the difference between these two measures deepens from (2.2) to (2.5) ("MP for IT - MP for non-IT" from 2.365 ($\chi^2 = 13.77$, $p - value = 0.00$) to 4.405 ($\chi^2 = 20.00$, $p - value = 0.00$) in Dataset I; and from 0.225 ($\chi^2 = 0.27$, $p - value = 0.60$) to 2.347 ($\chi^2 = 3.00$, $p - value = 0.08$) in Dataset II).

Results on CU Columns 4 and 7 in Figure 2.3 and Figure 2.4 present the estimates for our model on CU in (2.6). In Figure 2.3, Non-IT capital is negative and significant for both datasets ($\beta^u = -0.634$, significant at the 1% level in Dataset I, and -0.305, significant at the 5% level in Dataset II), while IT-capital is only negative and significant in the more recent dataset (i.e., Dataset II, $\gamma^u = -0.183$, significant at the 1% level). This partially answers our third research question: IT and non-IT capital both reduce the short-run CU rate, because their effects on capacity outweigh those on actual output. IT capital in Dataset I does not contain software, and software is likely to be indispensable in improving firms' productive capacity. As a result, our estimate for the output elasticity of IT for capacity may be underestimated, causing a roughly equivalent effect of IT capital on actual output and on capacity, such that its overall effect on CU is close to zero in Dataset I. Furthermore, when converted to dollar terms (Columns 4 and 7 in Figure 2.4), our results in the more recent dataset (i.e., Dataset II) show that one billion dollars of IT (non-IT) capital is associated with a 3.11% (0.31%) decrease in CU for an average industry, indicating the impact of IT capital on CU is about ten times of that of non-IT capital.

2.3.2 Pre-Internet vs. Post-Internet

Our first dataset covers a time span from 1987 to 1999, a time period that contains the commercialization of the Internet around 1994 and the e-commerce boom in the later 1990s. Given the revolutionary impact of the Internet on manufacturing and business, we divide Dataset I into two sub-periods: pre-Internet and post-Internet, in order to test if there are any structural differences in the way IT and non-IT capital were utilized in production. According to Hobbes' Internet Timeline 10.2 (Zakon 2011), business and media started to notice the Internet in 1994, and the Internet was commercialized in 1995 when NSFNET (National Science Foundation Network) was decommissioned, removing the last restrictions on the use of the Internet to carry commercial traffic. Therefore, we define 1987-1994 as the pre-Internet period and 1995-1999 as the post-Internet period in Dataset I. We then test autocorrelation and heteroscedasticity for the two sub-periods, following a similar approach as we did for the two original datasets. The test results suggest the presence of heteroscedasticity (He) for all three models in each sub-period, panel-specific autocorrelation (PSAR1) for the models of actual output and CU in the pre-Internet period and for the model of actual output in the post-Internet period, and common autocorrelation (AR1) for the rest of the models in each sub-period. To be consistent with our earlier analysis, we use FGLS implemented in Stata to estimate our models controlling for the same sector and year dummies as for the pooled dataset.

Figure 2.5: **Results for Pre- and Post-Internet periods - Output Elasticities**

	1987-1994			1995-1999		
	Actual Ouput †	Capacity ‡	CU †	Actual Ouput †	Capacity ‡	CU ‡
IT Capital	0.133 ***	0.014	0.112 ***	0.238 ***	0.095 **	0.074 **
	(0.013)	(0.023)	(0.026)	(0.019)	(0.042)	(0.032)
Non-IT Capital	0.037 ***	0.239 ***	-0.661 ***	0.048 ***	1.205 ***	-0.707 ***
	(0.011)	(0.072)	(0.071)	(0.017)	(0.098)	(0.074)
Labor	0.193 ***			0.173 ***		
	(0.01)			(0.015)		
Intermediate Inputs	0.627 ***			0.531 ***		
	(0.018)			(0.031)		
N	312	312	312	195	195	195

Notes. Log dependent variable and input variables. Feasible Least Squares estimation, control for IT-producing, IT-using, and the year dummies. Dummies and interaction terms are suppressed for brevity.

∗p<0.10, ∗∗p<0.05, ∗∗∗p<0.01. Standard errors in parentheses.

† control for panel-specific heteroskedasticity (PSHe) and panel-specific autocorrelation (PSAR1)

‡ control for panel-specific heteroskedasticity (PSHe) and common autocorrelation (AR1)

Figure 2.6: **Results for Pre- and Post-Internet periods - Marginal Products**

	1987-1994			1995-1999		
	Acutal Ouput †	Capacity †	CU ‡	Actual Ouput †	Capacity †	CU ‡
IT Capital	4.959 ***	0.628	17.360 ***	6.064 ***	2.887 **	7.000 **
	(0.485)	(1.031)	(4.03)	(0.484)	(1.276)	(3.027)
Non-IT Capital	0.051 ***	0.401 ***	-3.000 ***	0.086 ***	2.631 ***	-2.83 ***
	(0.015)	(0.121)	(0.322)	(0.031)	(0.214)	(0.296)
N	312	312	312	195	195	195

† Marginal products

‡ Marginal impact on industry-average CU per one billion dollar increase

*p<0.10, **p<0.05, ***p<0.01. Standard errors in parentheses.

Figure 2.5 (output elasticities) and Figure 2.6 (marginal products) present the results from the sample splits of the 1987-1999 dataset. The striking finding is that in our capacity model IT capital is significant at the 5% level in the post-Internet period ($\beta^c = 0.095$, $MP = 2.887$), but insignificant in the pre-Internet period, indicating that the commercialization of the Internet substantially boosts productive capacity, at least in our data. Moreover, IT capital has a positive and significant impact on CU in both sub-periods (pre-Internet: $\beta^u = 0.112$, significant at the 1% level, $MP = 17.36$; post-Internet: $\beta^u = 0.074$, significant at the 5% level, $MP = 7.0$). Recall that CU is the ratio of actual output over capacity. As IT capital only affects actual output in the pre-Internet period, it is not surprising that more IT is associated with higher CU rate in that period. In the post-internet period, however, IT capital begins to show substantial impact on capacity as well. As the magnitude of such impact may still be smaller than that on actual output, IT still has a positive and significant effect on CU overall. Finally, consistent with results from our original datasets, compared with non-IT capital, IT capital has a greater effect on capacity and CU in terms of marginal products.

2.3.3 Robustness Tests

Although our two datasets differ in time span, set of industries, level of aggregation, and definition for IT capital, our main results are still consistent across the two datasets and sample splits. To further check the robustness of our results, we carry out additional analyses using different econometric models and adjustments.

Estimates with Random Effects   Conceptually, random effects allow the omitted variables to vary over time. Random effects models are especially efficient if the industry-level effects change over time and possibly are correlated with our independent variables. We run the random effects model controlling for first-order autocorrelation, and the results are highly consistent with our baseline results, except that IT capital is not significant in either the capacity model or the CU model for the post-Internet period. We suspect this is because the random effects procedure does not control for panel-level heteroskedasticity, which is present in our data, and also possibly from multicollinearity and a loss of degrees of freedom (see Han, Kauffman and Nault 2011).

Endogeneity   Another potential issue with our estimation is the endogeneity of the independent variables, which mainly comes from three sources: omitted variables, measurement error, and simultaneity (Wooldridge 2002). There are possibly omitted variables and measurement error that are correlated with the independent variables. However, to the extent that these omitted variables and measurement error are serially correlated, our adjustments with panel-specific/common autocorrelation can help relieve this problem. The third potential source for endogeneity, simultaneity, arises when one or more of the independent variables are determined with the dependent variable. In our context, when profit maximizing firms observe demand shocks in the market (not observable to researchers), they choose the input levels accordingly.

Following Baum, Schaffer, and Stillman (2003), We use the two-step feasible generalized method of moments (GMM2s) procedure implemented in Stata in order to test if our independent variables are endogenous. In particular, one-year lags of the four input variables (i.e., IT capital, non-IT capital, labor, and intermediate inputs) as well as the interactions between the variable inputs and the industry dummies are used as excluded instrumental variables. The year dummies and sector dummies are assigned as the included instrumental variables. Controlling for arbitrary heteroskedasticity, we then run this procedure and conduct the associated endogeneity test to jointly test the exogeneity of our four input variables. The test statistic is defined as the difference between two Sargan-Hansen statistics: one for the equation where the suspect independent variables are treated as endogenous, and one for the equation where they are taken as exogenous. Under conditional homoskedasticity, this endogeneity test statistic is numerically equal to a Hausman test statistic (Hayashi 2000, 233-234). However, it is of particular interest in the context of heteroskedasticity (Baum et al. 2003). The test results show that we cannot reject the null hypothesis that the four input variables are exogenous for the capacity model and the CU model in Dataset II (Capacity model: $\chi^2(4) = 2.625$; CU model: $\chi^2(4) = 7.208$), in the pre-Internet period (Capacity model: $\chi^2(4) = 7.637$; CU model: $\chi^2(4) = 4.364$), and in the post-Internet period (Capacity model: $\chi^2(4) = 3.757$; CU model: $\chi^2(4) = 3.480$). However, this null hypothesis is rejected for both models in Dataset I (Capacity model: $\chi^2(4) = 17.323$; CU model: $\chi^2(4) = 11.513$). This is likely because our IT capital measure in this dataset does not contain software, and software may be more correlated with both output and other input factors such as non-IT capital and labor in the pooled dataset than in the sample splits. In order to control for this potential endogeneity problem, we perform a two-stage least squares procedure (2SLS) to estimate these two models for Dataset I, using two year lags of the four input variables and their interactions with the industry dummies as excluded instruments. All results are consistent with our major findings for Dataset I.

2.4 Discussion and Conclusion

Adopting the FRB's definition of productive capacity, we propose a two-state framework about how IT and non-IT capital constrain the short-run production expansion from an actual output level to a sustainable maximum level (i.e., capacity), and demonstrate strong empirical evidence to answer our three research questions. First, we find that IT capital has a significant contribution to capacity, and it is substantially different in magnitude compared with its contribution to actual output. This provides empirical evidence that IT, as the emerging general purpose technology, has a substantial impact on capacity besides its well-documented impact on actual output. Moreover, when both types of capital are utilized to their full potential, producing at capacity follows a different production process in terms of the productivity of the inputs as compared with production at a profit-maximizing level (i.e., actual output). Second, when producing at capacity we find that IT capital has a greater MP than non-IT capital, consistent with our results for actual output. Because both types of capital are fixed in the short-run, they become the constraints on capacity. Therefore, the MPs represent the shadow prices of the two types of capital, and our results imply that relaxing the IT capital constraint yields a higher payoff than non-IT capital when producing at capacity.

On the third and most fundamental question, our results show that additional non-IT capital helps to reduce CU in both of our datasets. However, IT capital only does so in the more recent dataset (i.e., Dataset II), and does not have a significant effect on CU in the earlier dataset (i.e., Dataset I). This means that although IT may improve production efficiency, its impact on capacity is relatively greater such that its overall impact on CU is significantly negative. Moreover, over the years IT's role has changed from simple automation and substitution towards enabling more organizational changes and making labor and non-IT capital more productive (Brynjolfsson and Hitt 2003, Mittal and Nault 2009). Thus IT's contribution to productive capacity gradually outweighs that to actual output as this transition of role deepens over time, causing its effect on CU to change from neutral to negative and significant. Finally, we show that the commercialization of the Internet and its applications in manufacturing and business have had a substantial impact on firms' sustainable maximum output, by finding the corresponding output elasticity of IT to be positive and significant in the post-Internet period as opposed to insignificant in the pre-Internet period. This is because internet-related technologies facilitate firms with better information sharing and coordination, thus enable them to better respond to demand and task uncertainties.

Contributions Our study of capacity and CU makes three important contributions. First, to the best of our knowledge, our work is the first to study short-run productive capacity and CU from a production perspective. That is, we examine how quasi-fixed inputs such as IT and non-IT capital affect capacity and CU. The majority of prior literature on capacity and CU takes into account the demand side variations and thus focus on the long-run planning of capacity and CU. Second, our study is the first to systematically explore the relationship between IT and capacity, as well as IT and CU. This opens doors for future research to this important but under-studied area. Current IT productivity literature concentrates on how IT contributes to actual output. However, as IT has become the next general purpose technology we found it has had a substantial impact on capacity, and more fundamentally, on CU. Third, we are able to show not only that IT and non-IT capital both have significant contributions to capacity, but also that IT capital is a more binding constraint on capacity than non-IT capital in the sense of having a substantially greater MP. We also find evidence supporting a transitional role of IT from raising the CU rate in the early days of application, possibly by increasing efficiency, to lowering CU over time as a consequence of becoming a more general-purpose technology with greater reach. These results have managerial and policy implications as we discuss below.

Managerial and Policy Implications There are critical managerial and policy implications of our findings. In our production function analysis, IT and non-IT capital are both long-run decisions. Once the capital in place is fixed, the maximum amount of variable inputs (i.e., labor and intermediate inputs) that can be used for production is determined and thus sustainable maximum output (i.e., capacity) is also determined. Therefore, when firms are planning for their optimal capacities over time, they need to first consider investment in IT and non-IT capital. What is more, our marginal products results show that additional investment in IT capital is associated with much larger returns in capacity than is non-IT capital. This suggests that managers should take advantage of the high marginal products for IT capital when considering a capacity expansion and increase their relative capital investments in IT. In addition, we have shown in our more recent dataset that IT capital has a substantially greater effect than non-IT capital on reducing the CU rate. Of course, depending on different profit rationales, there are many ways to change CU, such as changing output but not capacity by adjusting variable inputs. Nevertheless, if managers decide to lower their CU by making long-term adjustments on capital, they should invest more in IT capital such as software and computers and relatively less in non-IT capital. Finally, CU has long been a policy-related variable because of its predictive power for inflation, unemployment, etc. Our results on CU suggest that IT investments may partially be responsible for the low inflation rate since late 1990s.

Limitations First, our analysis is done at the industry level, and this constrains our ability to provide managerial implications since technology and input choices are made at the firm level. Industry-level analysis is more likely to suffer from aggregation error than firm-level, although such aggregation errors also exist when moving from product level to firm level. Despite the fact that our industry-level datasets are at different levels of aggregation and with different measures of IT capital, that we still obtain consistent results mitigates the chance that our results are driven by aggregation versus real effects between IT and capacity. Another limitation is that our data does not represent the whole economy. The majority of our data come from the manufacturing sector, and we recognize that the service industries may exhibit very different behavior when comparing actual output and capacity. An interesting future research path is to study these questions in the service sector. In addition, our earlier dataset does not contain software, and software is likely to be indispensable in improving firms' productive capacity. Therefore, our estimates for the output elasticities of IT for capacity may be under-estimated in this dataset.

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Chapter 3

ARE IT INVESTMENT ANNOUNCEMENTS INFORMATIVE? EVIDENCE FROM THE OPTION MARKET

3.1 Introduction

Are information technology (IT) investment announcements informative? In other words, do IT announcements provide new information to investors? If so, what do the IT announcements tell investors? When do the financial markets capture such informativeness of IT announcements? Which market captures the information better, the option market or the stock market? These questions regarding the informativeness of IT investments from the investors' perspective have not been the focus of prior research, and we answer these questions by providing new evidence from the option market.

Anything that causes investors to act can be described as information (Beaver 1968, Sun 2003). So, if an IT investment announcement is informative (i.e., has information content), then it should lead to a change in investors' assessment of expected future returns, such that there is an altering of the optimal holding of that firm's securities in the portfolios of individual investors. The optimal adjustment may include buying/selling the firm's securities, opening or closing an option contract written on the firm's stock, etc. Therefore, we can infer the informativeness of IT announcements from investors' actions around the announcement days. These actions would be reflected in the abnormal trading volume (Beaver 1968), which has been widely adopted by event studies (e.g., Ajinkya and Jain 1989, Sanders and Zdanowicz 1992, Donders, Kouwenberg and Vorst 2000, Jayaraman, Frye and Sabherwal 2001, Nofsinger and Prucyk 2003, Arnold, Erwin, Nail and Nixon 2006). In fact, the strength of this approach lies in the fact that it captures the overall actions by a large number of investors upon receiving new information from IT announcements. The idea is that, when an IT investment announcement is made, investors evaluate the public information contained in the announcement and then re-adjust their beliefs about the expected value and uncertainty of the announcing firm. According to the semi-strong version of the efficient market hypothesis (Fama 1970), the investors' beliefs about the expected value that the IT investments bring to the firm are immediately transformed to trading actions on the firm's securities, and thus may cause trading volume on the announcement day to be "abnormal", that is, deviate from predictions. For example, McDonalds Corporation (NYSE:MCD) has an average trading volume of 7.58 million shares per day. On December 17, 2002, they announced a warning and reduction of expected earnings (Sun 2003). The news led to trading of 35.17 million shares that day, about five times the average. Such an event is informative, and the informativeness of the event is exactly captured by the abnormal trading volume on the event day. Although there have been several studies that use trading volume to determine whether an event has informational content (e.g., Beaver 1968, Foster 1973, Karpoff 1986, Ajinkya and Jain 1989, Harris and Ravin 1993, and Donders et al. 2000), there has not been a study that systematically investigates whether IT investment announcements are informative. That is our main motivation.

Assuming traders are rational and there are no outside opportunities, a trading transaction becomes possible because the potential buyer and the potential seller have different expectations about the value of the underlying securities. From this perspective, changes in trading volume in response to IT announcements can be interpreted as a measure of investors' lack of agreement on their interpretations of the value of these events (Im et al. 2001). In fact, there are several distinct ways through which informational events affect trading volume (Beaver 1968, Karpoff 1986, Harris and Ravin 1993, and Donders et al. 2000). First, trading volume is higher if investors have divergent prior expectations. Second, receiving slightly different information increases trading volume. Third, even if investors have the same prior expectations and receive the same information, they may differ in the way they interpret the information and thus volume is further increased. Investors may differ in their beliefs about whether the information is favorable or unfavorable; or, they could disagree on the extent to which the information is important. Finally, if the investors receive the information sequentially, then trading volume increases because of the information asymmetry among investors. It is worthwhile to notice that change in trading volume gives no information about the direction of investors' valuation of the events. It just tells us that investors are reacting to the information, and the announcements are informative.

The event study method has been fruitfully applied in the information systems literature to study the impact of general IT investments (e.g., Dos Santos, Peffers, and Mauer 1993, Brynjolfsson and Yang 1997, Im, Dow, and Grover 2001, Subramani and Walden 2001, Chatterjee, Pacini, and Sambamurthy 2002, Dewan and Ren 2007), but few have concentrated on volume. Drawing upon a sample in the early 1990s, Chatterjee, Pacini, and Sambamurthy (2002) find significant positive abnormal trading volume associated with IT infrastructure investment announcements. Im et al. (2001) find insignificant abnormal trading volume for IT investment announcements, and suggest that this may be due to the fact that stock market investors on average have difficulties in interpreting the importance of IT announcements. Indeed, this is why we believe that a lack of understanding the true value of IT investments among the the equity market participants may cause the stock market investor to under-value IT investment and thus not able to capture the information conveyed by the IT announcements.

We propose using the option market as an alternative venue to the stock market to study the informativeness of IT for the following reasons. First, option market traders have been shown to be more informed than those in the stock market (Easley, O'Hara, and Srinivas 1998). Informed traders are more willing to trade in the option market as opposed to the equity market because investing in options provides more leverage and a thus a larger potential return than investing in the underlying stocks (Black 1975, Cao, Chen, and Griffin 2003). Therefore, we expect that the option market captures the information conveyed by IT announcements earlier than the stock market.

Second, even after announcements become public, investors's judgement of the same information may be different (Kim and Verrecchia 1994, Jin, Livnat, and Zhang 2012). The very nature of option trading requires, on average, a higher level of quantitative and analytical skills than stock trading, which may help with the valuation of complicated information input from IT announcements. In addition to the risk factors that an equity manager must control for, an option manager must consider expiration time, exercise price, and volatility risk, which requires on average more technical and analytical skills than standard equity trading. In fact, Jin et al. (2012) argues that "relative to equity traders, option traders have superior ability to process less anticipated information.[1]" (pg. 30) Consequently, given the complex nature of IT projects, we expect the responses to IT announcements from the option market to be greater in magnitude than those from the stock market. Overall, we believe that the stock market traders may be under-estimating the potential of IT investments, and that the option market may be able to better capture the informativeness of IT announcements.

Besides its more informed and quantitative nature, the option market helps improve our understanding of how investors react to the new information from IT announcements. Option traders could choose and even design the contract that match their expectations of risk and cash flows, however, stock market is not able to capture such divergent beliefs among investors. Each option contract has a expiration date when the contract expires. The length between trading date and expiration date is defined as the expiration length. Option contracts with longer (shorter) expiration lengths represent investors's beliefs about the

[1]Given the uncertainty about the exact price, the announcement date, the medium of exchange, and the likelihood of success of the IT projects, we believe that the events in our sample are not anticipated, and the possible pre-announcement trading should only be attributed to informed trading.

firm's future value in the long (short) run. Therefore, by studying option market's response to IT announcements, we are able to to tell if IT announcements are more informative to investors about the long-run value or the short-run value of the firm.

Furthermore, there is great value to studying the volume reaction in the option market. Trading volume has potential for testing hypotheses that are not addressable by the typical price returns methodology alone (Ajinkya and Jain, 1989). Easley et al. (1998) show both theoretically and empirically that option volumes can lead price movements in equity markets. Lending support to this finding, Pan and Poteshman (2006) provide evidence that put-call ratios in the option market predict price movements in equity markets. Moreover, abnormal trading volume has been used to detect insider trading and information leakage prior to actual announcement days (e.g., Keown and Pinkerton 1981, Sanders and Zdanowicz 1992).

In addition to abnormal trading volume, we test whether IT announcements are informative using open interest. An examination of the option market allows for the use of abnormal open interest as a measure of IT announcement informativeness. Open interest refers to the total number of outstanding option contracts for a specific underlying stock on a certain date. Open interest increases when there are new option contracts created on the underlying stock, and decreases when the existing option contracts expire or are closed out by investors. Option contracts can be traded without a change in open interest. In contrast, changes in open interest require contracts to be traded, except in the case of expirations. Open interest is often used as an indicator of the intensity of trading, and of the revealing of new information (Jayaraman, Frye and Sabherwal 2001). Compared with stock shares outstanding which are issued by the firms, open interest is endogenous in the sense that all the option contracts are initiated by investors. Therefore, open interest could provide additional evidence of the informational content of the IT announcements.

Motivated by what we present above, we explore four research questions. First, are

IT investment announcements informative in general? Second, when do the financial markets capture the informational content of IT announcements? Third, does the information conveyed by IT announcements differentially affect investors' beliefs about short-term and long-term future firm values? Fourth, what types of IT announcements are more informative? We answer these questions by calculating abnormal trading volume and open interest around e-commerce announcement days in the option market in the 1996-2002 time frame. For purpose of comparison, we also calculate abnormal trading volume for the stock market. Two factors distinguish our effort from those of previous research. First, we systematically investigate the informativeness of IT investment announcements - that is, whether IT announcements have informational content that causes investors to act. Second, we are the first to measure option market's response to IT announcements.

The remainder of the paper proceeds as follows. In the next section we present our model to calculate the abnormal trading volume and open interest. After that, we introduce our datasets and the specifications regarding estimation and calculation. Following that, we present our main results. The last section discusses our findings and contributions.

3.2 A Model of Abnormal Volume

We calculate the abnormal volume for the days in the event window to capture the response of financial markets to the IT announcements. The calculation of abnormal open interest follows the same procedure.

As raw trading volume data are highly non-normal, we begin by constructing a transformed volume variable,

$$V_{i,t}^{m} = ln(1 + volume_{i,t}^{m}),$$

where $volume_{i,t}$ is the total trading volume for the announcing firm in event i on day t. $m \in \{e, o\}$ represents the equity market (e) or the option market (o). Because the model is the same for the two markets, we do not address the meaning of m for the rest of this section unless necessary. Define $t = 0$ as the day when IT announcement i is made (e.g., the event day), $t < 0$ a day prior to the event day and $t > 0$ a day after the event day. The event window $[t_1, t_0]$ ($t_1 \leq 0 \leq t_0$) is the window of consecutive trading days immediately around the event day (including the event day). The estimation window $[t_3, t_2]$ ($t_3 < t_2 < t_1$; t_1, t_2, t_3 are negative integers) is the window of consecutive trading days before the event window.

Following a standard approach to calculate abnormal volume (Ajinkya and Jain 1989, Sanders and Zdanowicz 1992, Arnold et al. 2006), we first estimate the following form for each event over its estimation window:

$$\Delta V_{i,t}^m = \alpha_i^m + \beta_i^m \Delta V_{i,t-1}^m + \epsilon_{i,t}, \tag{3.1}$$

where $\Delta V_{i,t}^m = V_{i,t}^m - V_{i,t-1}^m$, and $t \in [t_3, t_2]$. α_i is the average change in trading volume between two consecutive trading days in the estimation window for event i, β_i is the one-year lag effect, and $\epsilon_{i,t}$ is the mean zero, normally distributed error term for the announcing firm in event i on day t. For the announcing firm in each event, we define the abnormal trading volume for each day in the event window, which is the difference between the actual volume and the predicted volume:

$$AV_{i,h}^m = \Delta V_{i,h}^m - [\hat{\alpha_i^m} + \hat{\beta_i^m} \Delta V_{i,h-1}^m], \tag{3.2}$$

where $h \in [t_1, t_0]$. $AV_{i,h}$ is the abnormal trading volume in day h in the event window for the announcing firm in event i. $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimates of α and β from (3.1). The variance of $AV_{i,h}$ is calculated as (Judge et al. 1998, pg.170; Subramani and Walden 2001, pg.144):

$$var(AV_{i,h}^m) = S_i^2 \left[1 + \frac{1}{T} + \frac{[\Delta V_{i,h-1}^m - \overline{\Delta V_i^m}]^2}{\sum_{t=t_3}^{t_2} [\Delta V_{i,t-1}^m - \overline{\Delta V_i^m}]^2} \right], \tag{3.3}$$

where S_i^2 is the variance of the error term from (3.1), T is the number of trading days in the estimation window (i.e., $[t_3, t_2]$), $\overline{\Delta V_i}$ is the mean value of $\Delta V_{i,t-1}$ over the event window. From (3.3), we can see that the variance of abnormal return by our definition depends on the length of the estimation interval, and the distance between the current value of the predictor and its mean value over the event window.

Following Sanders and Zdanowicz (1992), we then calculate the average daily abnormal volume across all events:

$$AAV_h^m = \frac{\sum_{i=1}^{N} \left[AV_{i,h}^m \ / \ var(AV_{i,h}^m) \right]}{\sum_{i=1}^{N} \left[1 \ / \ var(AV_{i,h}^m) \right]}, \tag{3.4}$$

where AAV_h is the average abnormal trading volume for day h ($h \in [t_1, 0]$) across events, N is the total number of events. The variance of AAV_h is:

$$var(AAV_h^m) = \frac{\sum_{i=1}^{N} \left[(AV_{i,h}^m - AAV_h^m)^2 \ / \ var(AV_{i,h}^m) \right]}{[N - 1] \sum_{i=1}^{N} \left[1 \ / \ var(AV_{i,h}^m) \right]}. \tag{3.5}$$

With (3.4) and (3.5), we are able to examine the statistical significance of the average abnormal volume using a student's t test, which is of the form:

$$\frac{AAV_h^m}{\sqrt{var(AAV_h^m)}} \sim t_{(N-1)}. \tag{3.6}$$

Then, we can use (3.4) and (3.5) to calculate the cumulative average abnormal volume (CAAV) for the event window or its sub-periods:

$$CAAV^m = \sum_{h=a}^{z} AAV_h^m, \tag{3.7}$$

where a and z are, respectively, the first and last days of the accumulation period in the event window or the sub-periods. $CAAV$ is the cumulative average abnormal volume over the days in the accumulation period. We can examine the statistical significance of the $CAAV$ using the statistic:

$$\frac{CAAV_h^m}{\sqrt{\sum_{h=a}^{z} var(AAV_h^m)}} \sim t_{(N-1)}. \tag{3.8}$$

Finally, in order to test if the difference between the $CAAVs$ for options and stocks is statistically greater than zero, we use the following student's t test:

$$\frac{CAAV_h^o \; - \; CAAV_h^e}{\sqrt{\frac{var(CAAV_h^o) \; + \; var(CAAV_h^e)}{N}}} \sim t_{(N-1)}. \tag{3.9}$$

Following the same procedure, we also calculate the cumulative average abnormal open interest, $CAAO^m$.

3.3 Data

We use the same list of 640 electronic commerce announcements as in Dewan and Ren (2007) [2]. This data is collected from PR Newswire and BusinessWire in Lexis-Nexis, and from four distinct years: 1996, 1998, 2000, and 2002. Events that have confounding factors such as earnings announcements and lawsuits have already been eliminated from the list [3].

Notice that in this list one firm can only make one announcement on one day, but can have several announcements on different days. In addition, one announcement only corresponds to one announcing firm on a particular day. Each announcement is treated as one event in our analysis. For the announcing firm in each event, we collect daily stock trading volume over the period beginning 120 trading days before the announcement date and ending 5 trading days after the announcement date. [4] For the same period and each event, we collect data on trading volume and open interest for option contracts written on the underlying firm's stock. Each firm on a specific day may have multiple contracts written with different expiration lengths and exercise prices. We aggregate the trading volume and open interest over all option contracts written on a firm on every day in the sample period.

The stock data is obtained from the Center for Research in Security Prices (CRSP), and the option data from the OptionMetrics database. The option data includes both put and call

[2] We thank Sanjeev Dewan and Fei Ren for sharing this data

[3] For a detailed description of the making of the event list see pg. 378 in Dewan and Ren (2007).

[4] If the announcement day is a public holiday, we use the next immediate trading day as the event day.

American options [5]. We drop events that either do not have corresponding traded options at all or do not satisfy our continuity test, which is done separately for the pre-announcement windows and the event windows. We drop events for which the pre-announcement windows have missing volume data for more than 30 trading days, or where two consecutive trading days are more than three calendar weeks apart, or if the total calendar duration for the window is more than 200 calendar days. We also drop events for which the event window contains missing volume data for more than 4 trading days, or where two consecutive trading days are more than three calendar days apart. Only events that satisfy these continuity tests for pre-announcement and event windows are selected into our final sample. The purpose of the continuity test is to further ensure our results are not driven by unobserved factors that may affect market's response to the IT events. Our final dataset is a balanced panel of 424 IT announcement events (49 in 1996, 86 in 1998, 150 in 2000, and 139 in 2002) across 126 relative trading days. A further description of the full sample is provided in Figure 3.1.

3.4 Results

In order to test whether the IT announcements are informative to investors prior to the announcement days, and if the volume response persists after the events, we include trading days both prior to and after the event day in the event window. Therefore, we adopt an event window starting ten trading days before (Dewan and Ren 2007) and ending five trading days after the announcement date (i.e., (-10,5)). The estimation window consists of the trading days prior to the event window (i.e., (-120,-11)). We do not include more trading days after the event day in the event window because we believe five trading days is enough for investors to incorporate the information from the announcements and behave accordingly. Moreover, the longer the window, the more confounding factors there may be that could bias our results. We divide the event window into four measurement windows and calculate

[5] European options are not traded on equities in the US.

the cumulative abnormal volume ($CAAV$) and cumulative abnormal open interest ($CAAO$) over each measurement window: (-10,-6), (-5,-1), 0, and (1,5), where (-10,-6) and (-5,-1) are two pre-announcement measurement windows, 0 is the event-day measurement window, and (1,5) is the post-announcement measurement window. We report $CAAV$ and $CAAO$ for each of the four measurement windows in each result table in section 4.

We focus on the significance of the pre-announcement trading activities and less on signs and magnitude, because until the announcements become public, traders continue acquiring private information and updating their beliefs, thus there is still uncertainty before the announcements as to how accurate the traders' opinions are (Ederington and Lee 1996). We pay attention to significance, sign as well as magnitude on and after the announcement days, assuming the information conveyed by the announcements have been absorbed by investors and are reflected in their trading activities.

3.4.1 Baseline Results

Our baseline results are reported in Figure 3.2, where the $CAAVs$ and $CAAOs$ are calculated using the full sample of 424 events. The trading volume for options are aggregated over all existing option contracts. The $CAAV$ is positive and significant on day 0 for the stocks ($CAAV = 0.064$, $t = 3.06$, $p < 0.01$), while the $CAAVs$ are not significant for call or put options. This suggests that, using the full sample, IT announcements are only informative to the stock traders on the event day. We do not observe significant response from the option market, likely because option traders only act on certain types of option contracts. Unlike stock shares, the option market traders may choose or even design the optimal contract that fits their beliefs about future expected return of the firm. This may lead to an uneven distribution of trading volume on different option contracts, and an insignificant aggregate response.

The $CAAOs$ are negative and significant for the two-week pre-announcement window (-10,-6) ($Call : CAAO = -0.034$, $t = -3.11$, $p < 0.01$; $Put : CAAO = -0.036$, $t = -3.22$,

Figure 3.1: **Summary Statistics**

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
Equity trading volume	55968	4475885	1379000	8662028	0	1.78E+08
Put option trading volume	55968	3084.152	166	8865.358	0	256554
Call option trading volume	55968	4528.843	434	11268.87	0	216281
Put option open interest	55968	81617.2	7389	195310.6	0	1431576
Call option open interest	55968	123177.9	14158	307085.4	0	2039523

Note. Summary statistics on the full sample with 424 events, covering four years: 1996, 1998, 2000, and 2002. The unit of measure is in number of shares (for volume) or number of contracts (for options).

Figure 3.2: **Base Results (on Full Sample)**

Abnormal Variable	Security type	Expiration Length	Number of events	Measurement Window			
				(-10, -6)	(-5, -1)	0	(1,5)
CAAV	Stock	Full Sample	424	0.043 (0.85)	-0.075 (-1.52)	0.064*** (3.06)	-0.052 (-1.06)
	Call	1-1000	424	0.073 (0.07)	-0.136 (-1.36)	0.004 (0.11)	0.017 (0.18)
	Put	1-1000	424	-0.081 (-0.71)	-.118 (-1.05)	0.048 (0.87)	-0.053 (-0.47)
CAAO	Call	1-1000	424	-0.034*** (-3.11)	0.002 (0.29)	-0.000 (-0.07)	-0.010 (-1.24)
	Put	1-1000	424	-0.036*** (-3.22)	0.009 (1.05)	0.003 (0.68)	-0.001 (-0.07)

Note. CAAO (Cumulative Average Abnormal Open Interest) and CAAV (Cumulative Average Abnormal Volume) are calculated for the measurement windows. The estimation window is (-120,-11).
Significance Level (two-tailed): *** 0.01 ** 0.05 * 0.10

$p < 0.01$), and insignificant for the windows after. This indicates the option market is able to capture the informational content of IT announcements prior to the event day, likely because informed traders choose to trade in the option market (Easley et al. 1998), and they close out their positions at least 5 days prior to the event day. Instead of trading existing option contracts, the informed traders should initiate new contracts or close out existing contracts in order to capitalize on their information advantage. This is why we observe significant $CAAOs$ in one of the pre-announcement windows.

3.4.2 Short Term, Mid Term, and Long Term

The results on $CAAV$ by expiration lengths are presented in Figure 3.3, where trading volume is aggregated over different expiration lengths. The most interesting finding is that the $CAAVs$ are mainly positive and significant for the options expiring between 1 to 30 days ($Call : CAAV = 0.120$, $t = 1.84$, $p < 0.1$; $Put : CAAV = 0.112$, $t = 1.76$, $p < 0.1$). This implies that IT announcements mainly affect investors' beliefs about short-term firm value, instead of long-term firm value. The reason may be that investors do not believe that most IT investments fundamentally change the nature and management of firms. It could also be a result of the time coverage of our datasets: the dot-com bubble burst towards the end of year 2000 adding more uncertainty to long-run expected firm value. Using the same list of 349 events, the $CAAV$ for stocks is also significant on the event day but with a much smaller magnitude ($CAAV = 0.063$, $t = 2.75$, $p < 0.01$), indicating that the option market is responding to IT announcements with a greater magnitude. We believe this is because the option traders can better interpret the information content of IT announcements.

There are a few significant results on $CAAV$ prior to the announcement days ($CallOptions1-30on(-10,-6) : CAAV = 0.275$, $t = 2.07$, $p < 0.05$; $CallOptions301-600on(-5,-1) : CAAV = -0.690$, $t = -1.76$, $p < 0.1$; $PutOptions101-300on(-10,-6) : CAAV = -0.332$, $t = -2.34$, $p < 0.05$), but no significant responses from the stock market in the pre-announcement windows. This again suggests that the option market captures the information from IT announcements ahead of the stock market. No result in the post-announcement window is significant, which means there is no delay in investors' actions upon observing the announcements.

Figure 3.4 reports the results on $CAAO$ by expiration length. Overall, there is more significance in all the measurement windows than in Figure 3.3, although the main message is the same. The response on the event day remains strongest in the short term, and gradually weakens in magnitude as the expiration lengths get longer, suggesting the IT announce-

Figure 3.3: **CAAV by Expiration Lengths**

Security type	Expiration Length	Number of events	Measurement Window			
			(-10, -6)	(-5, -1)	0	(1,5)
Stock	Matching Option 1-30	349	0.052 (0.94)	-0.059 (-1.11)	0.063*** (2.75)	-0.064 (-1.23)
Call	1-30	349	0.275** (2.07)	-0.160 (-1.27)	0.120* (1.84)	0.135 (1.06)
	31-100	365	0.026 (0.19)	0.030 (0.23)	0.070 (1.13)	-0.003 (-0.02)
	101-300	420	-0.096 (-0.72)	-0.123 (-0.95)	-0.054 (-0.96)	0.038 (-0.28)
	301-600	49	0.142 (0.37)	-0.690* (-1.76)	0.291 (1.60)	0.068 (0.17)
	601-1000	147	0.015 (0.07)	-0.141 (-0.69)	0.049 (0.54)	0.009 (0.04)
Put	1-30	349	0.065 (0.49)	-0.145 (-1.15)	0.112* (1.76)	0.034 (0.26)
	31-100	365	0.082 (0.57)	0.108 (0.73)	-0.101 (-1.2)	-0.072 (-0.50)
	101-300	420	-0.332** (-2.34)	-0.125 (-1.00)	-0.028 (-0.57)	-0.018 (-0.15)
	301-600	49	-0.151 (-0.29)	-0.633 (-1.15)	0.165 (0.62)	0.519 (0.88)
	601-1000	143	0.004 (0.01)	-0.139 (-0.50)	-0.018 (-0.16)	-0.061 (-0.21)

Note. CAAV (Cumulative Average Abnormal Volume) are calculated for the measurement windows.
The estimation window is (-120,-11).
Significance Level (two-tailed): *** 0.01 ** 0.05 * 0.10

ments are more informative to investors about short-term firm value than about long-term firm value. We observe significant $CAAOs$ for options with longer expiration lengths likely because creating new long-run positions is more beneficial to investors than trading existing long-run contracts. Moreover, there is strong evidence of informed trading prior to the event days, as well as significant changes in trading activities after the event days. The significant $CAAOs$ and insignificant $CAAVs$ in the post-announcement window imply that there is continued interest in the IT investment decisions announced, which is, however, mainly attributable to new positions opened and old positions closed out. Overall, Our results on $CAAO$ provide even stronger evidence about the informativeness of IT announcements than the $CAAV$ results. This is because open interest is an endogenous measure and thus able to give additional insights about investors' responses (Jayaraman et al. 2001).

Figure 3.4: **CAAO by Expiration Lengths**

Security type	Expiration Length	Number of events	Measurement Window			
			(-10, -6)	(-5, -1)	0	(1,5)
Call	1-30	349	-0.227** (-2.45)	0.138** (2.30)	0.09** (2.28)	0.072 (1.17)
	31-100	365	-0.071 (-0.59)	0.352*** (8.44)	0.065*** (2.96)	0.226*** (4.69)
	101-300	420	-0.321*** (-8.69)	-0.078*** (-2.80)	0.012* (1.92)	-0.325*** (-8.33)
	301-600	49	0.017** (2.19)	-0.002 (-0.22)	-0.001 (-0.75)	0.003 (0.72)
	601-1000	147	0.092*** (4.02)	0.082*** (4.92)	0.002 (0.68)	0.036** (2.15)
Put	1-30	349	-0.127 (-1.42)	0.080 (1.29)	0.084*** (2.57)	0.112* (1.83)
	31-100	365	-0.125 (-0.85)	0.422*** (8.65)	0.060*** (2.23)	0.231*** (4.10)
	101-300	420	-0.277*** (-7.77)	-0.264*** (-6.90)	-0.056*** (-3.37)	-0.397*** (-8.27)
	301-600	49	-0.003 (-0.50)	-0.012** (-2.09)	-0.006*** (-3.66)	-0.003 (-0.50)
	601-1000	143	0.113*** (4.44)	0.146*** (9.10)	-0.003 (-0.92)	0.040 (3.47)

Note. CAAO (Cumulative Average Open Interest) are calculated for the measurement windows. The estimation window is (-120,-11).
Significance Level (two-tailed): *** 0.01 ** 0.05 * 0.10

3.4.3 Good News, Bad News, and No News

Many empirical studies support the hypothesis that investor reactions differ to good and bad news (Schachter 1988). Thus, the observed pattern in volume and open interest around announcements may be the net effect of investors' anticipations of good and bad news. In order to determine the types of IT announcements that are more informative to investors, we assign each announcement to one of three types: good news, bad news, or no news. Following Campbell, Lo, and MacKinlay (1996), we categorize each announcement using an ex-post measure: the deviation of the actual return from the expected return on the announcement day. The calculation largely follows our model of abnormal volume, except that we use a market model to predict the returns. If the actual exceeds expected by more than 2.5% the announcement is designated as good news, and if the actual is more than 2.5% less than expected, then the announcement is designated as bad news. Those announcements where the actual returns are in the 5% range centered about the expected returns are designated as no news. Of our 424 announcements, 78 are good news, 92 are bad news, and the remaining 254 are no news.

Figure 3.5: **CAAV by News Type**

News Type	Security type	Number of events	Measurement Window (-10, -6)	(-5, -1)	0	(1,5)
Good News	Call	78	0.054	-0.011	0.432***	-0.407**
			(0.18)	(-0.06)	(5.27)	(-2.09)
	Put		-0.157	-0.068	0.442***	-0.318
			(-0.65)	(-0.30)	(3.12)	(-1.33)
	Stock		-0.039	-0.035	0.335***	-0.347***
			(-0.38)	(-0.36)	(7.44)	(-3.61)
Bad News	Call	92	0.207	-0.310	-0.185**	0.183
			(0.89)	(-1.26)	(-1.98)	(0.80)
	Put		0.024	-0.267	0.061	-0.146
			(0.09)	(-0.99)	(0.57)	(-0.57)
	Stock		0.128	-0.123	0.148***	-0.051
			(1.19)	(-1.20)	(2.95)	(-0.52)
No News	Call	254	0.035	-0.124	-0.099*	0.131
			(-0.25)	(-0.98)	(-1.87)	(1.02)
	Put		-0.087	-0.090	-0.110	0.078
			(-0.58)	(-0.61)	(-1.60)	(0.52)
	Stock		0.030	-0.042	-0.003	0.015
			(0.55)	(-0.76)	(-0.12)	(0.28)

Note. CAAV (Cumulative Average Abnormal Volume) are calculated for the measurement windows.
The estimation window is (-120,-11).
Significance Level (two-tailed): *** 0.01 ** 0.05 * 0.10

Our results on $CAAV$ by news type are reported in Figure 3.5. There are no significant responses in the pre-announcement windows for any of the new types. However, and most interestingly, we find that the good-news announcements are more informative than the bad-news and no-news announcements on the event day in terms of having significant and stronger

Figure 3.6: **CAAO by News Type**

News Type	Security type	Number of events	Measurement Window			
			(-10, -6)	(-5, -1)	0	(1,5)
Good News	Call	78	-0.026	0.043***	0.020***	-0.016
			(-1.35)	(3.33)	(3.81)	(-0.76)
	Put		-0.025	0.045***	0.019***	0.014
			(-1.30)	(3.08)	(2.92)	(0.73)
Bad News	Call	92	-0.024	0.008	-0.005	0.015
			(-1.12)	(0.42)	(-0.59)	(1.06)
	Put		-0.022	0.006	0.004	-0.002
			(-0.87)	(0.32)	(0.55)	(-0.14)
No News	Call	254	-0.035**	-0.008	-0.004	-0.016
			(-2.43)	(-0.71)	(-0.70)	(-1.50)
	Put		-0.040***	0.000	-0.002	-0.003
			(-2.73)	(0.07)	(-0.34)	(-0.25)

Note. CAAO (Cumulative Average Abnormal Volume) are calculated for the measurement windows.
The estimation window is (-120,-11).
Significance Level (two-tailed): *** 0.01 ** 0.05 * 0.10

response to the IT announcements ($GoodNewsCall : CAAV = 0.432$, $t = 5.27$, $p < 0.01$; $GoodNewsPut : CAAV = 0.442$, $t = 3.12$, $p < 0.01$; $GoodNewsStock : CAAV = 0.335$, $t = 7.44$, $p < 0.01$; $BadNewsCall : CAAV = -0.185$, $t = -1.98$, $p < 0.05$; $BadNewsStock : CAAV = 0.148$, $t = 2.95$, $p < 0.01$; $NoNewsCall : CAAV = -0.099$, $t = -1.87$, $p < 0.1$). Notice that the $CAAVs$ for options for the good-news announcements are also much greater in magnitude than those for stocks, as well as those for the short-term options in Figure 3.3. The strong response to good-news announcements indicate investors' preference towards IT announcements that raise their expectations about expected firm value. The negative $CAAV$ for call options for the bad-news announcements on the event day ($CAAV = -0.185$, $t = -1.98$, $p < 0.05$) is due to the fact that when investors have negative opinions about the IT investments, they are not enthused about the likelihood of success of these initiatives and would postpone trading call options and hold on to their portfolios. The no-news events barely convey any information so even the stock market traders are indifferent about them. Moreover, the $CAAVs$ are negative and significant for call options and stocks for the good-news announcements on (1,5) ($Call : CAAV = -0.407$, $t = -2.09$, $p < 0.05$;

$Stock : CAAV = -0.347; t = -3.61; p < 0.01$), which is likely because the trading activities on the event days are too large in magnitude such that the trading volume in the following days drop significantly relative to the event days.

Figure 3.6 presents the $CAAO$ results by news type. The main message from the $CAAO$ results is the same as that in Figure 3.5, confirming the good-news IT announcements being more informative on the event day than the other two types of announcements ($Call$: $CAAO = 0.020$, $t = 3.81$, $p < 0.01$; Put : $CAAO = 0.019$, $t = 2.92$, $p < 0.01$). As before, the $CAAO$ measure is able to capture the informativeness of IT announcements prior to the event days ($GoodNewsCallon(-5, -1) : CAAO = 0.043$, $t = 3.33$, $p < 0.01$; $GoodNewsPuton(-5, -1) : CAAO = 0.045$, $t = 3.08$, $p < 0.01$; $NoNewsCallon(-10, -6) : CAAO = -0.035$, $t = -2.43$, $p < 0.05$; $NoNewsPuton(-10, -6) : CAAO = 0.040$, $t = -2.73$, $p < 0.01$). The negative and significant $CAAOs$ in the two-week pre-announcement window (-10,-6) for the no-news type indicate a significantly decreased interest in the underlying firm from investors in the option market, due to the fact that the no-news IT announcements are not providing information to help them better understand future firm values.

3.4.4 Robustness

We re-ran all of our analyses shrinking the event window to one week on either side of the event (i.e., (-5,5)), and again using the trading days prior to the event window as the estimation window (i.e., (-120,-6)). In particular, we calculate $CAAVs$ and $CAAOs$ for three measurement windows: (-5,-1), 0 , and (1,5). We found that our main qualitative results remain unchanged.

3.5 Discussion and Conclusions

We study whether IT announcements are informative events. In particular, we adopt cumulative average abnormal volume (CAAV) and cumulative average abnormal open interest (CAAO) as measures for abnormal levels of trading activities in the option market around IT announcements. Our findings are consistent across trading volume and open interest, and across different sub-samples. There are four main messages from our findings. First, IT announcements indeed convey information to investors such that they act on the underlying securities. Such information tends to be captured by the option market prior to the event day, and continue to generate interest in the post-announcement trading days. Second, we exploit the fact that options have a term structure. This allows us to show that IT announcements mainly affect investors' expectations about short-term firm value, with less effects on expectations of long-term firm value. This distinction can only be captured by option market trading activities. Third, good-news IT announcements are more informative to investors than bad-news and no-news announcements. Fourth, compared to stock market traders, option market traders respond to IT investment announcements earlier, and with greater magnitude. Our findings can help firm executives and managers better understand the possible responses and assessments from financial markets to their IT investment announcements, and thus can improve firms' decision making regarding IT investments.

Our academic contribution is to systematically determine whether IT investment announcements are informative - specifically using the novel approach of measuring the option market's response to such IT announcements. We believe that future research may further exploit the differential response between option markets and stock markets to IT announcements. These differences may contain useful information about disentangling IT's affect on firm risk and firm cash flows.

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Chapter 4

DO IT INVESTMENTS IMPACT FIRM RISK? EVIDENCE FROM THE OPTION MARKET

4.1 Introduction

Do information technology (IT) investments impact firm risk? More specifically, do such investments increase or decrease firm risk perceived by the option market investors? As IT continues to be a major driving force for innovation, productivity, and economic growth, IT projects are becoming increasingly complex and IT capabilities are often unpleasantly hard to build and manage for the firms. Therefore, it is crucial to understand the impact of IT investments on risk at the firm level. The IS discipline has long been interested in IS-related risks such as user perceived risk (e.g., Pavlou and Gefen 2004, Nicolaou and McKnight 2006), investor perceived risk (e.g., Dewan and Ren 2007), security risk (e.g., Loch, Carr and Warkentin 1992), IT project risk (e.g., Alter and Ginzberg 1978, Kwon and Zmud 1987, Benaroch 2002), software risk (Charette 1989, Boehm 1991, Fairley 1994), business process risk (e.g., Kettinger, Teng and Guha 1997, Kliem 2000), etc. By design, these risk measures are at the user level, project level, business process level, etc. However, few studies (i.e., Dewan and Ren 2007; 2011) measure firm-level risk changes from IT investments. We adopt a new, forward-looking risk measure from the option market, which allows us to explore the impact of IT investments on both short-term and long-term firm risk. In particular, we use implied volatilities (IV) from exchange-traded option prices as our risk measure. IV represents the market's expectation of the underlying firm's average stock return volatility over the remaining duration of the option contract. Prior work is equivocal about whether IT should decrease or increase firm risk, and is silent regarding short versus long term effects on risk. On the one hand, IT enhances information processing and thus enables firms to better respond to demand and task uncertainties (Galbraith 1974) ; on the other hand, IT are inherently risky assets to build and manage (Wang and Alam 2007). The mixed support from prior literature motivates us to explore how exactly IT investments may affect firm risk perceived by option market investors.

The concept of risk in the management literature can be traced back to Knight (1921). In his work, situations with risk are those where the outcomes were unknown but governed by probability distributions known at the outset. Classical decision theory conceptualizes the risk of a decision alternative in terms of variation in possible outcomes, in their likelihoods as well as their subjective values (Arrow 1965). Contrary to the common understanding that risk is only about bad outcomes, it can be the downward or upward variation in expected outcomes. Broadly speaking, risk has been defined along four dimensions: size of loss, probability of loss, variance of returns, and lack of information (Tanriverdi and Ruefli 2004). IS researchers have been mainly interested in understanding the effects of the IS-related risks, as well as improving the management of which, in order to achieve a better economic outcome. Our focus, however, is on the relationship between IT investments and overall firm risk perceived by the option investors - a market-based perspective on whether IT investments change the distribution of future outcomes for a given firm.

In enterprise risk management, risk is defined as any possible event or circumstance that can have a negative influence on the enterprise (Enterprise Risk Management Committee 2003). This stream of research uses either expected loss, or conditional value at risk (CVaR), with its focus on losses that have serious economic consequence, as risk measures to provide flexibility in achieving risk management objectives (Bai, Krishnan, Padman and Wang 2012).[1] Benaroch (2002) separates two forms of IT investment risks for firms: risk arising in software development and risk arising outside the scope of software development. The former mainly refers to software development cost, and the latter primarily covers com-

[1]For a summary on risk measures in enterprise risk management, see Bai et al. (2012).

petitive risk and market risk.[2] Based on Benaroch's division of IT investment risks, we believe, to the extent that the option investors understand these risks, our measure of firm risk also has two major sources: risk related to the IT project (e.g., system implementation risk, risk with business process redesign) and risk arising outside the scope of the IT project (e.g., change in competitive environment). A potential change in firm risk that is triggered by an IT investment should be a result of changes in these two sources as perceived by investors.

Our study is closely related to the stream of research in IS literature that studies IT-induced firm risk. A large body of research in this domain uses historical stock return volatility as a measure of firm risk.[3] Two alternative measures for risk are adopted by Carter, Dark and Singh (1998) and Kothari, Laguerre and Leone (2002) respectively: the standard deviation of one-year daily stock returns following the investment, and the standard deviation of realized annual earnings over 5 years following the investment. They show that IT capital investments make a substantially larger contribution to firm risk than non-IT capital investments. Agrawal, Bharath and Viswanathan (2003) examine the relationship between technological change (measured by e-commerce announcements) and changes in a firm's stock return volatility, and find that both idiosyncratic and total volatility significantly increase after the events. Dewan, Shi and Gurbaxani (2007) define IT risk as the variability of returns on IT investment, which is increased by unexpected positive or negative outcomes. They find that IT capital investments make a substantially larger contribution to overall firm risk than non-IT capital investments. Dewan and Ren (2007) define systematic risk as the change in total firm risk that can be explained by change in market variance, and unsystematic risk as idiosyncratic firm risk. By analyzing abnormal trading activities around IT investment announcements, they find that both total and unsystematic risk show a significant post-event increase in 1998 and 2000, whereas systematic risk adjusts downward in 1996

[2] For a summary on these risks, see Benaroch (2002).

[3] For a review on the impact of corporate events on the historical volatility of stock returns, see section 2.3 in Dewan and Ren (2007).

and 2002. Dewan and Ren (2011) adopt two alternative risk measures: variability of stock returns and variability of analysts earnings estimates. They discover that IT investments are associated with an increase in both risk measures.

Overall Impact on Firm Risk There has been evidence supporting IT investments increasing or decreasing firm risk. Numerous studies showed that IT investments have significant positive contribution to firm performance and profitability.[4] In particular, IT has been shown to have intangible benefits such as improved customer service, higher product and service quality, more efficient business processes and better flexibility in coordination (Mukhopadyay, Rajiv and Srinivasan 1997, Brynjolfsson and Hitt 2000, Bharadwaj et al 2007). Moreover, information sharing among supply chain partners facilitated by Internet-based inter-organizational information systems (IOSs) reduces the uncertainty of transactions and mitigates the effects of demand shocks (Cachon and Fisher 2000, Lee, So and Tang 2000).

According to the information processing view of the firm (Galbraith, 1974), IT serves as a coordination mechanism, providing information that enables the firm to better and more quickly respond to unexpected challenges arising from the business and competitive environment. This leads to less uncertainty about firms' earnings volatility. Investments in IT also help firms avoid potential catastrophic losses resulting from liability suits such as fraudulent or careless security handling, and other environmental disasters (Bharadwaj, Bharadwaj, Konsynski 1999). Fornell, Mithas, Morgeson and Krishnan (2006) find that investment announcements about customer relationship management (CRM) are associated with lower stock volatility. Dewan and Ren (2011) show that "*increased IT investments combined with greater firm diversification results in higher returns and lower risk.*" (p370).

In contrast, there is substantive evidence showing that IT may increase firm risk. As stated in Introduction, this increase may be due to two major sources. The first is IT

[4]For a recent review, see Kohli and Grover 2008, and Mithas, Tafti, Bardhan and Goh 2012.

project risk, including implementation risk, management risk, business process risk, etc. In fact, the failure rate of IT projects have been high (Iacovou and Dexter 2005). These include failures to deliver a system, budget overruns, massive delays, or organizational rejections. Usually they are outcomes of cognitive limitations, management inattention, or mediocre skills to address observed problems (Lyytinen, Mathiassen, Ropponen 1998). Moreover, IT investments are difficult projects to manage, sometimes failing spectacularly, often falling short of management expectations, and sometimes succeeding spectacularly (Lyytinen and Hirschheim 1987, Kobelsky, Hunter and Richardson 2008). This makes it a arduous job for investors to predict the expected returns of such IT investments.

The second source of a potential increase in firm risk lies outside of the scope of a project, such as competitive risk and user perceived risk. Consumers may perceive online shopping for certain products risky, and if investors observe this, then that strengthens their perception about IT investments as risky actions taken by the firms (Agrawal et al. 2003). Furthermore, if investors believe that a certain firm's entering the online market would raise the level of competition (e.g., triggering a price war), then they would believe this investment is associated with substantially increased risk for the firm. Using Information Week 500 data on IT spending from 1992 to 1997, Kobelsky, Hunter and Richardson (2008) also find evidence that IT investments increase the volatility of future earnings. Increased stock return volatility is also been found in several other IS studies (Carter et al., 1998; Kothari et al., 2002; Dewan et al., 2007; Dewan and Ren, 2011), which are reviewed in the Introduction.

A good example of IT investment's impact on the uncertainty about future firm profitability is a manufacturing company making investment in digitally controlled machines. These machines are able to produce related but different products, whereas the non-digital machines in place are only able to produce one type of product. As a result of the investment in such a digitally controlled production line, the company is able to switch between different products on the same production line based on the demand fluctuations, and therefore reduces the uncertainty of future profitability. However, there are risks that come along with this investment. First of all, these new machines need to be seamlessly integrated into the existing production environment, and may cause the redesign of existing business processes. Second, the firm needs to train its employees to properly operate and manage the new machines, in order to reduce the man-made mistakes and increase work efficiency. All these may lead to increase short-term firm risk, which may be gradually reduced over time as a result of the experience effect.

Thus, the literature has suggested different directions for IT's impact on firm risk. On the one hand, IT greatly contributes to firm performance and profitability, and to reducing risk by enabling firms to better respond to market uncertainties. On the other hand, as argued by Wang and Alam (2007), IT capability is inherently risky as it is subject to implementation challenges, technological complexity, and innovative integration of IT investments with other organizational resources.

Effect of Firm Size Although we expect to have no overall effect on the uncertainty of firms' future returns, we believe the impact of IT announcements on firm risk may depend on firm size. We consider the impact of size on the two major sources of firm risk: IT project risk and risk beyond the scope of IT project. In general, smaller firms are less experienced with handing IT investment projects. Also, due to their smaller size, a greater portion of a smaller firm is usually affected by IT projects than a larger firm. Thus, smaller firms are more vulnerable to IT project risk, being exposed to more fundamental changes in business models, management, and firm structures for smaller firms than for larger firms. Moreover, spending on IT projects usually accounts for a larger proportion of the overall budget for smaller firms, and thus exposing the firms to more risks considering the possibility of project failures.

Besides project risks, there are risks beyond the scope of the project itself. Smaller firms are more likely to fail when exposed to the online competition (Kobelsky et al, 2008). In addition, announcements made by smaller firms may contain more new information about firm earnings than for larger firms - making them more likely to surprise the investors (Bamber 1986, Wang 1994, Im et al 2001). Consequently, we expect IT investments to have a greater impact on the risk of smaller firms.

Effect of IT Investment Type   Following Dewan and Ren (2007), we explore the risk effects along three dimensions: *new* electronic commerce initiative versus *expansion* of an existing application; *Digital* goods or services versus *tangible* goods; and *B2C* versus *B2B* electronic commerce applications. Similar to Dewan and Ren (2007), we draw our theoretical support from the organizational learning literature (Winter 1971, Levinthal and March 1981, March 1991, and Kane and Alavi 2007) which identify two different types of firm activities: "exploration" and "exploitation". The idea is that, the "exploration" activities are systematically associated with more uncertainty in future returns than the "exploitation" activities, because the former involves the development of new knowledge while the latter is mainly incremental learning based on existing knowledge. We classify new e-commerce initiatives, digital goods e-commerce initiatives, and B2C applications as exploration activities, and the remaining three types of e-commerce events (i.e., expansion, tangible goods, and B2B) as exploitation activities. We anticipate that the exploration activities are associated with greater increase in risk than the exploitation activities.

Effect of News Type   Finally, we expect there exits a news type effect that moderates the impact of IT announcements on firm risk. A good news announcement is an event for which the actual stock return is more than the expected stock return upon the information being released, and a bad news announcement is one where the actual stock return for the underlying firm is less than the expected stock return. Controlling for such news type allows us to control the role of returns on firm risk. We examine the two types of news separately because prior literature suggests that changes in volatilities around information releases may be asymmetric between the two types (Black 1976, Campbell and Hentschel, 1992, Skinner 1994, Kothari et al., 2009, Rogers et al., 2009). First, good news IT announcements mean that the investors believe the information conveyed in the announcement is "better" than they expect, and thus gives them more confidence about the firm's future returns. Bad new announcements, however, surprise investors in a negative way and thus create more doubts about future firm returns. Second, Skinner (1994) suggests that managers disclose bad news when they know for sure that current period earnings news is adverse. In our case of IT investment announcements (instead of earnings announcements), however, it may just be the opposite. Firms tend to announce an IT investment project if they expect it to increase its market value and reduce return uncertainty. In fact, if an investment in IT is likely to result in an increase in risk (i.e., volatility of future stock returns), firms and their managers may just willingly forgo higher returns to avoid increased risk (Kobelsky et al., 2008). Therefore, bad news IT announcements should be more surprising to investors than good news IT announcements are. Therefore, we expect IT announcements that convey bad (good) news increases (decreases) firm risk.

We study four research questions in this paper. First, what impact do IT investment announcements have on firm risk? Second, does firm size affect IT's impact on firm risk? Third, does such impact depend on the explorative nature of IT investments? Fourth, does IT's impact on firm risk depends on whether the announcement conveys good news or bad news? We adopt implied volatilities (IV) derived from exchange-traded equity options as our risk measure, which represents the average variance or volatility of a firm's stock returns over the remaining duration of the option. The IV is a forward-looking measure compared with historical volatility, which is usually what is measured using stock market returns. Risk by this definition is subjective as it measures the uncertainty about investors' expectation of future firm value. We find that IT investment announcements increase firm risk, especially the short-term risk. However, there is a significant decrease in long-term firm risk associated with tangible goods e-commerce announcements. To the best of our knowledge, we are the first to distinguish between and study the long-term and short-term firm risk induced by IT investments.

Methodologically, we adopt an event study approach and measure the change in firm risk around the IT announcement dates for the full sample as well as for the sub-samples by firm size, by type of e-commerce investments, and by news type. The idea is that, when an IT investment announcement is made, investors evaluate the public information contained in the announcement and then re-adjust their beliefs about the expected value and uncertainty of the announcing firm. According to the semi-strong version of the efficient market hypothesis (Fama 1970), the investors' beliefs about the expected value of the firm is immediately reflected in the prices of its traded securities. As a result, we expect to detect a significant change in IV around the events if the investors indeed believe the IT investments being announced will increase or decrease the uncertainty about firms' future returns. To our knowledge, we are among the first studies that measure the IT event-induced firm risk and explore its determinants.

The rest of the paper is organized as follows. In the next section, we describe our datasets and research design. We then present our descriptive and empirical results. The last section discusses our findings and contributions.

4.2 Data and Research Design

4.2.1 Data

Our original list of 640 electronic commerce announcements is adopted from Dewan and Ren (2007).[5] This data is collected from PR Newswire and BusinessWire in Lexis-Nexis, and from four distinct years: 1996, 1998, 2000, and 2002. Events that have confounding factors such as earnings announcements and lawsuits have already been eliminated from the list (see

[5] We thank Sanjeev Dewan and Fei Ren for sharing this data

Dewan and Ren 2007, P378). In this list one firm can at most have one announcement on one day, but can have several announcements on different days. In addition, one announcement corresponds to only one announcing firm on a particular day. Each announcement is treated as one event in our analysis.

We adopt implied volatilities (IV) derived from exchange-traded equity options as our measure for firm risk. IV is an ex-ante measure because it is the market's expectation of the firm's average stock return volatility over the remaining time of an option contract. In contrast, realized volatility is an ex-post measure and thus is not forward-looking. Moreover, realized volatility has to be measured over some period of time, while IV can be measured on a daily basis, facilitating their use in short time intervals around information events.

The IV data are collected from the *OptionMetrics* database, where IV is derived from the hypothetical at-the-money-forward standardized options. Standardized options are built on a daily basis, to be at-the-money and of constant maturity, which reduces measurement error that arises from using options that vary in duration and in the extent to which they are in the money (e.g., Dumas, Fleming and Whaley 1998; Hentschel, 2003; Rogers et al., 2009).[6] We collect IV data derived from both call and put standardized options for the announcing firm in each event from 10 days before to 10 days after the event.[7] To access both short and long term firm risk, we collect IV data for options with 7 different expiration lengths: 30, 60, 91, 182, 365, 547 and 730 calendar days. We further drop 3 events because we could not match the underlying firms with the firm identifiers in OptionMetrics, which leave us with 637 announcements (68 announcements in the year of 1996, 151 in 1998, 215 in 2000, and 203 in 2002).

In order to test if firm size plays a role in determining the change in firm risk, we collect the "number of employees (EMP)" variable from the Compustat North American database and match it with our options datasets. In addition, to calculate the abnormal returns for

[6] For more information on the calculation of IV by *OptionMetrics* see http://wrds.wharton.upenn.edu/ds/optionm/manuals/IvyDBReference.pdf.

[7] If the announcement day is a public holiday, we use the next immediate trading day as the event day.

each event in order to determine if the event is a good news or bad news, we collect stock prices for the underlying firm for each event from 10 days before to 10 days after the event from the CRSP (Center for Research in Security Prices) database. The price data is also matched with our options datasets. Finally, we divide our full sample into different sub-samples based on the three dimensions we discussed earlier: *new* versus *expansion*, *digital* versus *tangible*, and *B2B* versus *B2C*. The coding of events was based on the analysis of the full text of the announcements. For a complete description of the coding see Dewan and Ren (2007), p380.

4.2.2 Research Design

A stream of IS literature examines the short-run reactions of the stock market to IT investment announcements by measuring the changes in stock price and trading volume (e.g., Dos Santos, Peffers, and Mauer 1993, Brynjolfsson and Yang 1997, Im, Dow, and Grover 2001, Subramani and Walden 2001, Chatterjee, Pacini, and Sambamurthy 2002, Dewan and Ren 2007). Among these studies, the most commonly adopted approach to calculate the abnormal return or abnormal volume is based on a the deviation of an actual value from its "predicted" value. This predicted value is usually estimated from a series of historical data. In the case of IV, however, this method is not used to forecast IV due to the nature of IV: rather than being directly available it is derived from option prices. Thus, we follow the convention from the Accounting literature (e.g., Sheikn 1989, Rogers et al. 2009) that applied to our context, and measure the impact of IT announcements on firm risk by calculating the change in IV around the events as specified below.

$$\Delta IV^i = ln(\frac{IV^i_{post}}{IV^i_{pre}}) = ln(IV^i_{post}) - ln(IV^i_{pre}). \tag{4.1}$$

Thus, the change in IV (ΔIV) is constructed as a log difference between IV from 5 days after the event (IV^i_{post}) and IV from 5 days before the event (IV^i_{pre}), where i represents a particular event. We are able to examine the statistical significance of ΔIV using a one-sample t-statistic:

$$\frac{\overline{\Delta IV}}{sd(\Delta IV)\ /\ \sqrt{N}} \sim t_{(N-1)}, \tag{4.2}$$

where $\overline{\Delta IV} = \frac{1}{N}\sum_{i=1}^{N} \Delta IV^i$, $sd(\Delta IV)$ is the sample standard deviation across events, and N is the number of events. This one-sample t-test is based on the assumption that every observation of ΔIV^i is drawn from an independent normal distribution that governs the distribution of risk change for the underlying firm in event i. When ΔIV^i is positive (negative) and statistically significant, there is evidence for an increase (decrease) in firm risk due to IT announcement i.

By design, IV is a perceived risk, which has been studied by IS researchers. For example, Pavlou and Gefen (2004) define risk as the belief of a potential tangible loss when transacting with the community of sellers in the marketplace. Nicolaou and McKnight (2006) define perceived risk as the extent to which one believes uncertainty exists about whether desirable outcomes will occur, and argues that one has to accept some risk to adopt a data exchange system, because transactions may or may not go as expected. Dewan and Ren (2007) study IT-induced risk perceived by stock market investors, and find that total firm risk increases after the e-commerce announcements in 1998 and 2000, but not in 1996 and 2002.

However, IV is distinct from the prior perceived-risk measures in the following ways. First, as suggested before, IV is a forward-looking risk measure. That is, IV is an ex-ante measure of the actual stock return volatilities. Therefore, IV is a direct measure of option investors' perception at a certain point in time about future volatility of the underlying stock. Second, IV has a term structure and thus allows us to study the both the short-term risk and long-term risk (i.e., risk over different time durations). As Brynjolfsson and Hitt (2003) show, it takes time to see IT-induced complementary organizational changes. Therefore, IV serves as a time-dependent measure to test if investors also consider this lag in time to observe some of IT's intangible effects. Third, IV is an aggregate risk measure because it is an overall reflection of the investors' perception about all possible risks that face the firm. Finally, as a perceived measure of risk by option market investors, IV may be a more accurate measure of the actual risk than a perceived risk measure by stock market investors. This is because the very nature of option trading requires, on average, a higher level of quantitative and analytical skills than stock trading, which may help with the valuation of complicated information input from IT announcements.[8] In fact, Jin, Livnat and Zhang (2012) argues that "relative to equity traders, option traders have superior ability to process less anticipated information." Consequently, given the complex nature of IT projects, we expect option investors's perception of firm risk may be more accurate than a similar perception of risk from stock market participants.

We perform a "continuity test" on each of our 7 raw datasets with different expiration lengths (i.e., 30, 60, 91, 182, 365, 547, and 730 calendar days). The continuity test checks if the 11-day interval (i.e., [-5, 5]: from 5 trading days before to 5 trading days after the event date) around each event has sufficient valid IV data. An event is dropped if the announcing firm does not have traded options for the interval at all, or if two consecutive trading days in the 11-day interval are more than 4 calendar days apart, or if the 11-day interval contains missing IV data for more than 4 trading days. Only events that satisfy such continuity tests are selected into our final sample. The purpose of the continuity tests is to further ensure our results are not driven by unobserved factors that may affect market's response to the IT events. Our final datasets are 7 balanced panel datasets which contain IV for both call and put options, number of employees, and stock prices. Each event has a proper 11-day window around the event date. Further descriptions of the datasets are provided in Figure 4.1.

[8] In addition to the risk factors that an equity manager must control for, an option manager must consider expiration time, exercise price, and volatility risk, which requires on average more technical and analytical skills than standard equity trading.

4.3 Results

4.3.1 Descriptive Results

Figure 4.1: **Summary Statistics**

Expiration Length	# of events	IV		Number of employees		Stock return		Percentage of negative ΔIV
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Call								
30	428	0.640	0.329	41.726	87.089	0.000	0.058	0.533
60	428	0.628	0.319	41.729	87.178	0.000	0.058	0.544
91	428	0.612	0.306	41.986	87.387	0.000	0.056	0.584
182	318	0.556	0.256	53.109	97.877	0.000	0.049	0.541
365	210	0.486	0.184	70.842	112.472	0.001	0.041	0.567
547	209	0.484	0.175	70.348	112.808	0.001	0.041	0.541
730	179	0.488	0.167	69.280	122.118	0.001	0.044	0.564
Put								
30	428	0.648	0.324	41.726	87.089	0.000	0.058	0.526
60	428	0.635	0.315	41.729	87.178	0.000	0.058	0.509
91	428	0.619	0.301	41.986	87.387	0.000	0.056	0.528
182	318	0.566	0.263	53.109	97.877	0.000	0.049	0.535
365	210	0.493	0.192	70.842	112.472	0.001	0.041	0.533
547	209	0.491	0.186	70.348	112.808	0.001	0.041	0.522
730	179	0.493	0.182	69.280	122.118	0.001	0.044	0.564

Notes.
All summary statistics are based on our final datasets that passed the continuity test, so the number of events are always less than 637.
The contituity test is to make sure that each event has a proper estimation window (i.e., 5 days before and 5 days after the event), for details please see Research Design.
IV is the average implied volatility across estimation windows and across events.
Number of employees is the average number of employees (in thousands) across the underlying firms of the events.
Stock return is the average stock return across estimation windows (i.e., [-5,5]) and across events.
ΔIV = ln (IV_post/IV_pre)
IV_pre= Implied Volatility from 5 trading days before the event
IV_post=Implied Volatility from 5 trading days after the event

A description of our 7 datasets (i.e., with expiration lengths 30, 60, 91, 182, 365, 547, and 730 calendar days respectively) after the continuity tests are presented in Figure 4.1. We describe call and put options separately because they have different IV. The number of qualified events for each expiration length is always less than 637 because some events do not pass our continuity tests and thus are dropped from the list. In particular, the number of qualified events is 428 for expiration lengths 30, 60, 91, and decreases monotonically as expiration length becomes longer, to 179 events for the length of 730. This decrease in the number of qualified events shows that in general, fewer investors trade long-term options because it is harder to estimate the long-run impact of an IT investment.

The mean value of IV ranges from 0.640 (call) and 0.648 (put) to 0.484 (call) and 0.491 (put), and generally diminishes as expiration length gets longer. In contrast, overall the average number of employees in a firm increases with expiration length: from around 41700 to around 70000 employees. This indicates that longer time to expiration options are traded on larger firms. The stock return for each event is calculated as the mean return for the underlying firm over the [-5, 5] day window. We report the average stock return across events for each dataset, which is consistently close to zero. We also calculate the percentage of negative log ratio (i.e., $ln(IV_{post}/IV_{pre})$) across the events for each option type in each dataset. This percentage is consistently around 0.55 for all our datasets, which suggests that about half of the qualified events in our samples are associated with an decrease in IV. Under the assumption that the log ratio for the underlying firm in every event follows an independent normal distribution, our job is to explore if the mean of these distributions is statistically different from zero.

4.3.2 Empirical Results

The analysis is executed for each of our 7 datasets with different option expiration lengths (i.e., 30, 60, 91, 182, 365, 547, and 730 calendar days). The longer expirations are necessary because investment in IT may take years to add value to a firm (Bharadwaj, Bharadwaj, and Konsynski, 1999). Assuming option market investors understand this, they would make adjustments to their beliefs about long-run firm risk compared to short-run risk. To make sure that our results are robust and are not driven by unique factors about put or call options alone, we calculate the log ratios using IVs derived from both put and call options. Below we first present our baseline empirical results and then the results for different sub-samples.

Baseline Results

We present our baseline evidence on IV changes around IT investment announcements in Figure 4.2. The log ratios of IV from 5 days after and before the event date are presented in Column 3 and Column 4, and the corresponding t-statistics in Column 5 and Column 6. Overall, there are statistically significant increases in IV around the IT announcements (except for call options with the 547 day expiration length). The put and call options generate highly symmetric results. The change in IV is greater for short duration options, and gradually declines as the duration gets longer (For call options IV, the increase is greater than 1.0% for the expirations of 182 days and less; and less than 1.0% for expirations longer than 182 days; for put options IV, the threshold for 1.0% increase moves up to 365 days). Our results indicate that IT announcements increase firm risk, especially firm risk in the short-term. This suggests that, despite all the potential benefits from IT, investors view IT capabilities as risky assets to build and manage (Wang and Alam, 2007). Our divisions of the full sample would help us better understand what factors contribute to this overall increasing risk perceived by options investors.

Size Effect

In order to access the size effect on the change in firm risk. We divide our full sample of 637 events at the 60th percentile value of the EMP variable (i.e., number of employees). We choose the 60th percentile value of EMP (i.e., 15500 employees) as the threshold because the continuity test drops more events that belong to smaller firms, and including slightly more firms in the "small" group ensures that we have a more balanced sample size between the "small" and "large" sub-samples after the continuity test. In fact, when we re-run all the analyses using the 50th percentile value of EMP (i.e., 6580 employees) as the threshold, our main qualitative results remain the same. Notice that our division of "small" and "large" sub-samples is only relative, many "small" firms really are not that small based on number

Figure 4.2: **Base Results**

Expiration length	# of events	ln (IV_post/IV_pre)		t-statistic	
		Call	Put	Call	Put
30	428	0.018**	0.018**	2.20	2.27
60	428	0.017**	0.019***	2.51	2.97
91	428	0.017***	0.019***	2.96	3.48
182	318	0.012**	0.017***	2.33	3.34
365	210	0.009*	0.010**	2.06	2.42
547	209	0.006	0.009**	1.47	2.26
730	179	0.008*	0.009**	1.68	2.17

Notes.
Each expiration length represents the group of standardized options that would expire in the exact length of calendar days.
Number of events is the total number of events that passed our continuity test.
The log ratio and t statistics are calculated at the event level.
IV_pre= Implied Volatility from 5 trading days before the event
IV_post=Implied Volatility from 5 trading days after the event
***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed).

of employees. Also, to be consistent, we use one threshold value to divide the full sample instead of using different threshold values for different expiration lengths.

The results are presented in Figure 4.3. The log ratios are reported in Column 4 and Column 5, and their t-statistics in Column 6 and Column 7. We find statistically significant changes in IV around the event days for the "small" firm sub-samples, except for call options that have a longer time to expiration: 365 or 547 days. However, the "large" firm sub-samples do not have any significant changes in IV around the event days. This finding supports our expectation. It means that the IT investments in our sample only affect the uncertainty about the underlying firm value for the smaller firms. We suspect this is because, as we described earlier, smaller firms are more likely to undergo fundamental changes that come along with their IT investments, while larger firms may be less affected overall. Moreover, the log ratios for the smaller firm sub-sample is much greater than those in our baseline results table (Figure 4.2), indicating the baseline results are in part driven by the smaller

Figure 4.3: **Results by Size**

Expiration length	Firm size	# of events	ln (IV_post/IV_pre)		t-statistic	
			Call	Put	Call	Put
30	Small	220	0.026***	0.032***	2.85	3.50
	Large	208	-0.003	-0.003	-0.22	-0.28
60	Small	220	0.018**	0.023***	2.38	3.02
	Large	208	0.004	0.006	0.37	0.70
91	Small	220	0.021***	0.024***	3.02	3.59
	Large	208	0.003	0.007	0.32	0.82
182	Small	127	0.016**	0.023***	2.45	3.82
	Large	191	0.003	.007	0.39	1.06
365	Small	44	0.011	0.013**	1.32	2.16
	Large	166	0.003	0.004	0.55	0.86
547	Small	45	0.007	0.015**	0.94	2.34
	Large	164	0.002	0.003	0.46	0.73
730	Small	54	0.015*	0.023***	1.70	2.80
	Large	125	0.002	0.001	0.32	0.23

Notes.
Each expiration length represents the group of standardized options that would expire in the exact length of calendar days.
Number of events is the total number of events that passed our continuity test.
The log ratio and t statistics are calculated at the event level.
IV_pre= Implied Volatility from 5 trading days before the event
IV_post=Implied Volatility from 5 trading days after the event
small: Number of Employees < 15.5 (in thousands), 60th percentile value in the full sample of 640 events.
large: Number of Employees > 15.5 (in thousands), 60th percentile value in the full sample of 640 events.
***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed).

firms.

Effects of Types of E-commerce investments

In order to test the risk effects of the different types of e-commerce investments, we divide our full sample based on Dewan and Ren (2007). Among our 637 events, 424 are coded as B2C and 209 as B2B (4 are unclassified); 503 are coded as digital goods initiatives and 126 as tangible goods (8 are unclassified); 416 are coded as new initiatives and 209 as expansion (12 are unclassified). The unclassified events are due to insufficient information in the announcements. Figure 4, 5 and 6 reports our results for the B2B versus B2C, Digital versus Tangible, and New versus Expansion, respectively. In each Figure, log ratios are reported in Column 4 and Column 5, and their t-statistics in Column 6 and Column 7.

Figure 4.4: **B2B vs. B2C**

Expiration length		# of events	ln (IV_post/IV_pre) Call	ln (IV_post/IV_pre) Put	t-statistic Call	t-statistic Put
30	B2B	143	0.023*	0.023*	1.82	1.85
	B2C	285	0.012	0.012	1.36	1.25
60	B2B	143	0.022**	0.024**	2.25	2.42
	B2C	285	0.011	0.009	1.47	1.14
91	B2B	143	0.023***	0.026***	2.79	3.02
	B2C	285	0.011	0.010	1.63	1.53
182	B2B	103	0.015*	0.020***	1.99	2.84
	B2C	215	0.008	0.009	1.38	1.48
365	B2B	70	0.009	0.010	1.17	1.39
	B2C	140	0.005	0.008	1.06	1.61
547	B2B	69	0.006	0.010	0.81	1.34
	B2C	140	0.005	0.007	1.00	1.63
730	B2B	55	0.013*	0.018*	1.85	1.95
	B2C	124	0.006	0.006	1.12	1.46

Notes.
Each expiration length represents the group of standardized options that would expire in the exact length of calendar days.
Number of events is the total number of events that passed our continuity test.
The log ratio and t statistics are calculated at the event level.
IV_pre= Implied Volatility from 5 trading days before the event
IV_post=Implied Volatility from 5 trading days after the event
***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed).

B2B vs. B2C B2B e-commerce announcements significantly increase short-term firm risk (i.e., for expiration lengths 30, 60, 91, and 182) and partially increase the long-term risk (i.e., for the expiration length of 730). However, we find no evidence that B2C announcements have any impact on firm risk. This tells us that investors believe B2B investments are more risky than B2C investments in our sample period. A possible explanation is that B2B e-commerce development is more complex than B2C IT projects due to the more complex nature of B2B transactions involving more than one organization (Ordanini and Pol, 2001), and more complex IT projects may be perceived to be associated with more risks by the investors.

Figure 4.5: **Digital vs. Tangible**

Expiration length		# of events	ln (IV_post/IV_pre) Call	ln (IV_post/IV_pre) Put	t-statistic Call	t-statistic Put
30	Digital	339	0.017**	0.017**	2.05	1.99
	Tangible	89	0.012	0.006	0.72	0.45
60	Digital	339	0.018***	0.017**	2.61	2.31
	Tangible	89	0.004	0.002	0.29	0.15
91	Digital	339	0.018***	0.018***	3.12	2.87
	Tangible	89	0.000	0.005	0.02	0.45
182	Digital	250	0.013**	0.015***	2.31	2.74
	Tangible	68	0.003	0.004	0.30	0.37
365	Digital	165	0.012**	0.013***	2.44	2.86
	Tangible	45	-0.016*	-0.011*	-1.98	-1.85
547	Digital	164	0.009**	0.012***	2.05	2.74
	Tangible	45	-0.012*	-0.008*	-1.78	-1.93
730	Digital	146	0.010**	0.013***	2.15	2.69
	Tangible	33	-0.002*	-0.004*	-1.70	-1.79

Notes.
Each expiration length represents the group of standardized options that would expire in the exact length of calendar days.
Number of events is the total number of events that passed our continuity test.
The log ratio and t statistics are calculated at the event level.
IV_pre= Implied Volatility from 5 trading days before the event
IV_post=Implied Volatility from 5 trading days after the event
***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed).

Digital vs. Tangible As expected, the digital goods initiatives significantly increase firm risk both in the short-term and in the long-term, with the magnitude of such risk effect decreasing over time. Surprisingly, the tangible goods initiatives are associated with significantly reduced firm risk in the long-run (for expiration lengths 365, 547, and 730). This suggests that investors understand that tangible goods initiatives are by nature exploitive instead of explorative, and expect no change in firm's return volatility in the short-run. However, and more interestingly, they trust these tangible goods e-commerce applications to reduce the return uncertainty for firms in the long-run, when the online channel becomes a stable complement to the traditional distribution channels. This result is consistent with Brynjolfsson and Hitt (2003)'s finding that, the effects of IT-induced complementary organizational changes[9] take time to show.

Figure 4.6: **New vs. Expansion**

Expiration length		# of events	ln (IV_post/IV_pre)		t-statistic	
			Call	Put	Call	Put
30	New	301	0.022**	0.021**	2.46	2.32
	Expansion	127	0.005	0.007	0.40	0.50
60	New	301	0.018**	0.017**	2.41	2.23
	Expansion	127	0.009	0.010	0.89	0.89
91	New	301	0.017***	0.017**	2.66	2.51
	Expansion	127	0.011	0.014	1.26	1.50
182	New	209	0.011*	0.014**	1.77	2.22
	Expansion	109	0.009	0.012	1.15	1.52
365	New	131	0.008*	0.011**	1.71	2.30
	Expansion	79	0.002	.0034	0.25	0.51
547	New	130	0.004	0.009*	0.75	1.87
	Expansion	79	0.005	0.007	0.96	1.13
730	New	126	0.006	0.011*	1.11	1.99
	Expansion	53	0.009	0.008	1.63	1.45

Notes.
Each expiration length represents the group of standardized options that would expire in the exact length of calendar days.
Number of events is the total number of events that passed our continuity test.
The log ratio and t statistics are calculated at the event level.
IV_pre= Implied Volatility from 5 trading days before the event
IV_post=Implied Volatility from 5 trading days after the event
***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed).

New vs. Expansion Our results for the new versus expansion sub-samples match well with our expectations. We find new e-commerce initiatives significantly increase firm risk, especially short-term risk (i.e., for expiration lengths 30, 60, 91, 182, 365, and partially 730), while there is no risk effect for the expansions. As described before, this is due to the fact that new e-commerce announcements are more explorative in nature and thus perceived to be more risky.

[9] These include changes in organization structure, business processes, innovations in customer and supplier relations, etc.

Impact of News Type

We follow a modified method from Campbell, Lo, and MacKinlay (1996) to divide the full sample of events into "good news" and "bad news" sub-samples. Specifically, we categorize each announcement using the deviation of the actual stock return from the expected stock return on the announcement day. The calculation largely follows a standard abnormal returns model (Dos Santos, Peffers, and Mauer 1993; Dewan and Ren 2007). If the actual exceeds expected returns (i.e., the abnormal return is positive), then the announcement is designated as a good news, otherwise the announcement is designated as a bad news. Among our 637 announcements, 312 are good news, and the remaining 325 are bad news.

Figure 4.7: **Results by News Type**

Expiration length	News type	# of events	ln (IV_post/IV_pre)		t-statistic	
			Call	Put	Call	Put
30	Good News	218	0.005	0.006	0.45	0.62
	Bad News	210	0.031***	0.029**	2.76	2.53
60	Good News	218	0.007	0.010	0.75	1.20
	Bad News	210	0.026***	0.028***	2.85	2.94
91	Good News	218	0.006	0.009	0.80	1.22
	Bad News	210	0.027***	0.030***	3.50	3.63
182	Good News	167	0.004	0.006	0.59	0.95
	Bad News	151	0.021***	0.028***	2.79	3.87
365	Good News	117	0.005	0.004	0.88	0.74
	Bad News	93	0.015**	0.018***	2.06	3.01
547	Good News	117	0.001	0.002	0.20	0.38
	Bad News	92	0.013*	0.019***	1.98	3.34
730	Good News	101	0.001	0.002	0.12	0.29
	Bad News	78	0.016**	0.019***	2.43	3.59

Notes.
Each expiration length represents the group of standardized options that would expire in the exact length of calendar days.
Number of events is the total number of events that passed our continuity test.
The log ratio and t statistics are calculated at the event level.
IV_pre= Implied Volatility from 5 trading days before the event
IV_post=Implied Volatility from 5 trading days after the event
Good News = SAR (stock abnormal return) > 0
News News = SAR (stock abnormal return) < 0
***, **, and * indicate significance at the 1%, 5%, and 10% level (two-tailed).

Figure 4.7 reports the results for the two sub-samples. The log ratios are reported in

Column 4 and Column 5, and their t-statistics in Column 6 and Column 7. There is highly consistent evidence that bad news IT announcements significantly increase firm risk both in the short-run and in the long-run, while good news has no effect on firm risk. It again shows that investors view new IT capabilities as risky assets for the firms - the volatility of their expectations about future firm value substantially increases after the bad news announcements. Moreover, investors respond with caution to good news IT announcements: there is no significant change in IV around these events, which is likely because good news are less surprising than bad news given managers' incentive to report good news and hide bad news. Besides, we find that the magnitude of volatility change tend to be greater for shorter expiration lengths than for longer lengths (i.e., the average log ratios for expiration lengths 30, 60 and 91 for the bad news are 2.8% (call) and 2.9% (put); the average log ratios for expiration lengths 365, 547, and 730 for the bad news are 1.5% (call) and 1,9% (put)). Our division of news type allows us to control for the return effect on firm risk.

4.3.3 Robustness Tests

For certain IT announcements, it may take the investors less time to understand their value and take actions. To examine whether our analyses are sensitive to the length of interval that centers on the event dates, we re-ran all of our analyses using IV from 3 trading days before and after the event dates, and all the qualitative findings in our results remain unchanged. We do not use 1 trading day before and after because the news may be leaked to public just before the event date, and it may take some investors longer than a day to absorb the information conveyed by the announcements. In addition, different thresholds of firm size may affect the average firm size for the sub-samples. In order to test if our results are robust to different thresholds of firm size, we divide our full sample into "small" and "large" sub-samples at 5.828 which is the 50th percentile value among the 637 events. Our qualitative findings based on our results again do not change.

If the abnormal return of an announcement is close to zero, it may be "neglected" by investors and thus have no risk effect. Therefore, we need to make sure that our results are not driven by these announcements. To examine this, we further categorize an announcement as a good news only if the actual return exceeds the expected return by more than 5.0%, and as a bad news if the actual return is more than 5.0% less than the expected return. Those announcements where the actual returns are in the 10% range centered about the expected returns are designated as no news. Of our 637 announcements, 73 are good news, 75 are bad news, and the remaining 485 are no news. We find that the results are highly significant across all expirations for the bad news events, not significant at all for the good news events, and only rarely significant for the no news events. This confirms our major finding that the impact of IT investment on firm risk is dependent on the news type.

4.4 Conclusion and Discussion

We study how IT investment announcements impact firm risk. In spite of the large literature on IS event studies that mostly focus on price or volume reactions to IT announcements, little has been studied about IT investments' impact on firm risk. We examine the impact on firm risk by directly measuring the change in firm risk around e-commerce announcements in the 1996-2002 time frame. Specifically, we adopt an investor-perceived risk measure - implied volatility (IV) - derived from exchange-traded equity options. IV represents the expected average volatility of stock returns over the remaining option duration, and thus is an aggregate, forward looking measure of risk. Moreover, the term structure of options allows us to study both short-term and long-term risks. IV is also a more accurate risk measure than a perceived risk measure by stock market investors due to the quantitative skills advantage of option market traders. We measure the impact of firm risk by the log ratio of IV from 5 day trading days after to IV from 5 trading days before the event date.

We have five major findings. First, statistically, IT announcements significantly increase firm risk as investors believe new IT capabilities are inherently risky, although for more than 40% of events IT announcements decrease firm risk. Second, firm size is negatively associated with IT announcements' impact on firm risk. In particular, IT announcements made by smaller firms significantly increase firm risk while those made by larger firms have no effect. This is likely because smaller firms are more subject to fundamental changes brought about by the new IT initiatives. Third, we find that tangible goods initiatives reduce the long-run firm risk, likely because in the long-run, the online channels help firms rely less on the traditional channels and thus reduce firms' profitability uncertainty. Fourth, we find that bad-news IT announcements are associated with significantly higher firm risk, whereas good-news IT announcements have no effect. This may be due to the fact that bad-news announcements tend to be more surprising to investors, as well as their impression about the riskiness of new IT capabilities. Finally, the increase in IV is in general found to be greater for options with shorter expiration lengths than those with longer expirations, indicating that in general, investors believe firms will be able to gradually resolve the risks as their experience with IT capabilities grow over time.

Our findings have important implications for the managers. Although e-commerce announcements have been shown to generate positive abnormal returns for firms (e.g., Subramani and Walden 2001; Dewan and Ren 2007), we discover that these announcements also increase both short-run and long-run firm risk, especially for smaller firms, bad-news announcements, new initiatives and digital goods initiatives. The managers need to balance the gain in the short-run firm value versus the higher volatility of future returns in order to make a decision about making an e-commerce announcement. For researchers, one interesting future research path is to study the cross-sectional determinants of the IT announcement-induced firm risk. Another research direction is to explore the risk effects of the IT investments in other fields such cloud computing and health care.

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Chapter 5

CONCLUSIONS

In this thesis, we study the nature and value of IT from two perspectives. One is to view IT as one of the production inputs under the production function framework, and we explore its contribution to productive capacity - the maximum level of output by increasing labor and intermediate inputs to a maximum but sustainable level, as well as its contribution to CU. The other perspective is to view IT as a strategic investment decision made by the firms, and we are interested in understanding whether such IT events are informative - provide new information to investors, and how they alter investors' risk perceptions about the firms. Many studies in IS have explored the contribution of IT to actual output (e.g., Brynjolfsson and Hitt 1996, 2000, 2003; Cheng and Nault 2007, 2011; Mittal and Nault 2009), but prior research has not focused on IT's impact on the potential maximum level of output - productive capacity. Our first essay aims to fill this gap. Our second and third essays both study option market responses to IT investment announcements but have distinct concentrations. Our second essay systematically explores the informativeness of IT investment announcements, and is the first to measure option market's response to IT announcements in the field of IS. The impact of IT investments announcements on firm risk is examined in our third essay. We are first to use a forward-looking risk measure from the option market, which allows us to separate short-term and long-term firm risk.

The first essay conceptually and empirically demonstrate IT's impact on capacity as well as its utilization rate. We find that IT, as the emerging general purpose technology, has a substantial impact on capacity besides its well-documented impact on actual output. Moreover, when both types of capital are utilized to their full potential, producing at capacity follows a different production process in terms of the productivity of the inputs as compared with production at a profit-maximizing level (i.e., actual output). We are also able to show that IT capital is a more binding constraint on capacity than non-IT capital in the sense of having a substantially greater marginal product. This implies that relaxing the IT capital constraint yields a higher payoff than non-IT capital when producing at capacity. Our results on CU show that although IT may improve production efficiency, its impact on capacity is relatively greater such that its overall impact on CU is significantly negative. Finally, we discover that the commercialization of the Internet and its applications in manufacturing and business have had a substantial impact on firms' sustainable maximum output or productive capacity. Our results suggest that, when the goal is to increase industry-level capacity, the government may provide more incentives for industries to invest in IT capital than in other types of capital.

The second essay explores the nature of IT investment announcements - whether they are informational events. We calculate abnormal trading volume and abnormal open interest as measures for abnormal levels of trading activities in the option market around such IT announcements. Our findings are consistent across trading volume and open interest, and across different sub-samples. Specifically, we find that IT announcements convey new information to investors such that they act on the underlying securities. Such information tends to be captured by the option market prior to the event day, and continue to generate interest in the post-announcement trading days. We also exploit the term structure of options, and show that IT announcements mainly affect investors expectations about short-term firm value. Furthermore, we show that good-news IT announcements are more informative to investors than bad-news and no-news announcements. Finally, option market traders respond to IT investment announcements earlier, and with greater magnitude compared with stock market traders. Our findings may help firm executives better understand the consequences of their IT investment decisions in the financial markets, and thus may help with better decision making for the firms.

The third essay examines how IT investment announcements impact firm risk. We measure the impact on firm risk by directly calculating the change in firm risk around our sample of e-commerce announcements. Our main finding is that IT announcements significantly increase firm risk as investors believe new IT capabilities are inherently risky to build and manage. Specifically, IT announcements significantly increase firm risk only for the smaller firms. This is likely because smaller firms are more subject to fundamental changes brought about by the new IT initiatives. We also find that tangible goods initiatives reduce long-run firm risk. Furthermore, we show that bad-news IT announcements are associated with significantly higher firm risk, whereas good-news IT announcements have no effect. Finally, in general, options with shorter expiration lengths are associated with a greater increase in firm risk than those with longer expirations.

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APPENDIX

Figure 5.1: **Dataset I (1987-1999) - Three-digit SIC industry description**

1987 SIC Code	Industry Description
20	Food and kindred products
21	Tobacco products
221-4	Broadwoven fabric mills, cotton, wool, silk, and manmade fiber
225-7,9	Knitting mills, carpets and rugs, dyeing, finishing and miscellaneous textile goods
228	Yarn and thread mills
23	Apparel and other finished products made from fabrics and similar material
243-5,9	Millwork, plywood, and structural members, Wood containers and misc. wood products, Wood buildings and mobile homes
25	Furniture and fixtures
261	Pulp mills
262	Paper mills
263	Paperboard mills
265,7	Paperboard containers and boxes Converted paper products except containers
27	Printing, publishing, and allied industries
281	Industrial inorganic chemicals
282	Plastics materials and synthetics
283-5,9	Drugs, soap, cleaners, and toilet goods, Paints and allied products, Miscellaneous chemical products
286	Industrial organic chemicals
287	Agricultural chemicals
29	Petroleum refining and related industries
301	Tires and inner tubes
302,5,6	Rubber products, plastic hose and footwear
308	Miscellaneous plastics products, nec
31	Leather and leather products
321-3	Glass and glass products
324	Hydraulic cement
325-9	Stone, clay, and misc mineral products, Concrete, gypsum, and plaster products
331,2	Blast furnaces and basic steel products; Iron and steel foundries
34	Fabricated metal products, except machinery and transportation equipment
351-3	Engines and turbines, Farm and garden machinery; Construction and related machinery

354-6,8,9	Metalworking machinery and equipment; Special industry machinery; General industrial machinery and equipment; Refrigeration and service industry machinery; Industrial machinery nec.
357	Computer and office equipment
363,5	Household appliances, Household audio and video equipment
366	Communication equipment
371	Motor vehicles and equipment
372	Aircraft and parts
373	Ship and boat building and repairing
374-6,9	Railroad equipment, motorcycles, bicycles, Guided missiles and space vehicles, Miscellaneous Trans. Equipment
38	Measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks
39	Misc. manufacturing industries

Figure 5.2: **Dataset II (19982007) - Three-digit NAICS industry description**

2002 NAICS Code	Industry Title
211	Oil and Gas Extraction
212	Mining (except Oil and Gas)
213	Support Activities for Mining
311,312 (311FT)	Food and beverage and tobacco products
313,314 (313TT)	Textile mills and textile product mills
315,316 (315AL)	Apparel and leather and allied products
321	Wood products
322	Paper products
323	Printing and related support activities
324	Petroleum and coal products
325	Chemical products
326	Plastics and rubber products
327	Nonmetallic mineral products
331	Primary metals
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
336	Transportation Equipment
337	Furniture and related products
339	Miscellaneous manufacturing

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