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Are New IT-Enabled Investment Opportunities Diminishing for Firms?

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Today, few firms could survive for very long without their computer systems. IT has permeated every corner of firms. Firms have reached the current state in their use of IT because IT has provided myriad opportunities for firms to improve performance and, firms have availed themselves of these opportunities. Some have argued, however, that the opportunities for firms to improve their performance through new uses of IT have been declining. Are the opportunities to use IT to improve firm performance diminishing? We sought to answer this question. In this study, we develop a theory and explain the logic behind our empirical analysis; an analysis that employs a different type of event study. Using the volatility of firms' stock prices to news signaling a change in economic conditions, we compare the stock price behavior of firms in the IT industry to firms in the utility and transportation and freight industries. Our analysis of the IT industry as a whole indicates that the opportunities for firms to use IT to improve their performance are not diminishing. However, there are sectors within the IT industry that no longer provide value-enhancing opportunities for firms. We also find that IT products that provided opportunities for firms to create value at one point in time, later become necessities for staying in business. Our results support the key assumption in our work.

Key words: information technology industry; business value of IT; event study; stock price volatility; financial market evaluation; IT and firm performance, macroeconomic news; IT value
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1. Introduction

The focus of IS research has, from the very outset, concentrated on issues and problems directly related to the identification, selection, development, and implementation of new IT-enabled opportunities available to firms. For example, IS research has provided insights into the adoption of new technology (Brancheau and Wetherbe 1990, Dos Santos and Peffers 1998, Gurbaxani 1990) and application development and implementation processes (Ågerfalk et al. 2009, Delone and McLean 2003, Dickson et al. 1977, Venkatesh et al. 2003). In the segment of IS research concerned with the economics of IT, there is agreement that IT has helped improve productivity (Brynjolfsson 1993) but no consensus that IT adds value to firms. Some studies have found a positive relationship between IT investments and firm performance (Mukhopadhyay et al. 1995, Ranganathan and Brown 2006), whereas others have documented that IT investments have no effect on performance (Hitt and Brynjolfsson 1996, Prasad and Harker 1997).

Anderson et al. (2006) claim that public interest in the economics of IT has shifted from the macro-level benefits of IT (Brynjolfsson 1993) to a debate about firm-level benefits (Melville et al. 2004). One side of the debate claims that firms no longer benefit from IT investments because common standards for hardware, software, communications, and business applications reduce gains from new uses of IT (Bhatt and Grover 2005).[1] Proponents argue that standardization makes it easier for firms to duplicate a new IT application or IT architecture deployed by a competitor, potentially reducing first-mover benefits (Dos Santos and Peffers 1995) or IT architecture-related advantages (Bhatt and Grover 2005). This line of reasoning suggests that standardization reduces the incentive for firms to make opportunistic IT investments. The other side of the debate claims that the value of standardized IT products to competing firms differ because firms' processes and key resources are not identical (Clemons and Row 1991, Radhakrishnan

[1] We use the term new uses of IT to include any IT investments that will enable a firm to change its products, services, or processes in response to new opportunities or threats (e.g., investments in new IT applications, a new IT architecture, etc.).

et al. 2008), nor are their IT management capabilities (Mata et al. 1995). Proponents argue that firms continue to find new IT investment opportunities because standardized products have different impacts across competing firms (Wade and Hulland 2004). This line of reasoning suggests that the incentive for firms to make new IT investments will not disappear as long as IT prices keep decreasing or new IT products keep appearing. This debate raises an interesting question: are the new IT-enabled opportunities that are available to firms diminishing? Conversely, are IT investments by firms increasingly focused on existing IT use? The answer to this question is important because, although IT accounts for less than 7% of the U.S. economy, new uses of IT are a key driver of innovation in the U.S. economy (Brynjolfsson and Saunders 2010). Between 1995 and 2007, 50 to 75% of venture capital funding went into IT firms (Brynjolfsson and Saunders 2010).

We are unaware of any study that has sought to determine whether new IT-enabled opportunities available to firms are decreasing. To date, most of the IT value theories (Mata et al. 1995, Melville et al. 2004) and empirical studies (Chatterjee et al. 2002, Dewan and Ren 2007, Im et al. 2001) have attempted to answer firm and/or application-specific questions. For example, does a firm benefit from a new IT investment (Banker et al. 1990)? Do firms benefit from deploying a specific type of IT application (Ranganathan and Brown 2006)? How can firms benefit from new IT investments (Radhakrishnan et al. 2008)? In contrast, we seek to answer a more macrolevel question: as a whole, are investments in new IT uses diminishing?

This study is based on a theoretical model that links economic conditions to the IT investments made by firms, and thereby, to the demand for the products and services offered by IT industry firms (hereafter, referred to as "IT firms"). This theory and empirical study are based on the key assumption that the investments necessary to operate a firm are less discretionary than the investments aimed at new opportunities or threats. Thus, investments in new IT uses are more discretionary than the investments in IT operations (i.e., to keep systems that enable current IT use running). This theory suggests that when economic conditions change, the demand for the products and services (hereafter, products) of IT firms is affected differently if investments in new IT uses are decreasing than if they are not decreasing. This assumes that firms will not invest in new uses if IT does not provide performance-enhancing opportunities. As a consequence, changing economic conditions will have a smaller effect on the stock prices of IT firms if investments in new IT use are decreasing. By observing the response of the IT industry stock prices to changing economic conditions over time, we are able to determine the direction (decreasing or increasing) of investments in new IT use. In addition, we test our key assumption with three data sets, each involving a different segment of the IT industry: (1) a segment that provides products that are necessities for its customers; (2) a segment that provides products that are discretionary for its customers; and (3) a segment that provides products that have, over time, transitioned from being discretionary expenditures to necessary expenditures for its customers.

The data we used spans the period from 1980 to 2007 and includes all IT firms. Our main result shows that firms' investments in new IT uses *are not* diminishing. Moreover, our results also provide strong support for our key assumption; our analysis indicates that some IT sectors now offer products that are necessary expenditures for their customers, whereas other sectors provide products that are discretionary investments for their customers. Our analysis also reveals that an IT product that is a discretionary investment at one time may become a necessary investment later.

This study makes three significant contributions to the IS literature: (1) it is the first empirical study to demonstrate that new opportunities for firms to use IT to improve performance are not diminishing; (2) it presents a theory and empirical approach that could be useful in addressing issues of interest to IS and other business-research communities; (3) it shows that sectors of the IT industry can, over time, transition from providing firms with performance-enhancing opportunities to providing products/services that become necessities for their customers.

In the next section we develop the theoretical model and present our hypotheses. We then describe the method, data, and analysis and present the results. Finally, we discuss the results, conclusions, limitations, and potential for further research.

2. Theory and Hypotheses

2.1. IT Investment Categories

We classify investments made by firms into two categories: current business investments (CBIs) and new initiative investments (NIIs).[2] CBIs are expenditures that are necessary to sustain a firm's current operation, to sustain cash flow from its existing business model, and consequently, to affect current performance. Driven by opportunities and threats, NIIs seek to improve future performance. NIIs may enable a firm to expand operations, change the way it will operate in the future, or even completely change the firm's direction. NIIs typically do not immediately affect current performance.

[2] We use the term investment to refer to any type of spending.

In an IT context, CBIs are necessary to sustain the IT applications in current use (often referred to as IT operations). These IT outlays are necessary for a firm to exploit its current capabilities. For example, an anticipated increase in sales may cause a firm to invest in IT products in order to handle an increase in transaction volume. If a firm discovers an IT security breach, it may have to incur expenses to recover from the breach and to protect itself from similar breaches in the future. If a firm fails to make these investments, IT may not be able to sustain the firm's operational needs. To exploit current capabilities and generate cash flow from the current business model, firms have to maintain their current IT applications, provide support for these applications, and make the necessary investments to keep current systems secure.

NIIs enable firms to respond to an opportunity or threat. For example, consider a firm that is planning to implement a CRM application in order to better understand consumer preferences. Although such an application can favorably affect a firm's future demand, it is not required to run the firm today. However, over time, such an NII may mature and become necessary for the firm (i.e., become a CBI). For example, a CRM application that was initially conceived for market segmentation may be integrated with the firm's demand forecasting and inventory processes, thus becoming an indispensable component of the firm's daily operations. When this happens, the expenditures needed to sustain the CRM application becomes a CBI because this outlay is now necessary for the firm to keep operating in its usual way. Further, an IT application can be a NII for one firm and a CBI for another. Thus, whether an expenditure is a NII or a CBI depends on the firm and the point in time at which the expenditure is incurred.[3]

2.2. IT Investment Priorities

The history of IT use by firms indicates that a CBI is a higher priority than a NII. In the late 1970s and early 1980s, IT executives commonly complained that maintenance costs were consuming IT budgets, leaving few funds for new applications (Ewers and Vessey 1981). The situation at the time is epitomized by the statement (Ewers and Vessey 1981, p. 33), "Information Systems (IS) is facing a dilemma: software is absorbing an ever-increasing proportion of the total IS budget while maintenance is absorbing an ever-increasing proportion of the software budget, in the not-too-distant future, unless this trend is arrested, or reversed, nearly all software resources may be required for maintenance."

Management literature also supports this assertion. Successful firms leverage current competencies and *exploit* current products for stability (March 1991, Tushman and O'Reilly 1996). At the same time, they adapt to environmental changes, explore new ideas or processes, and develop new products for emerging markets. Firms tend to focus on exploitation at the expense of exploration (Benner and Tushman 2003). The exploitation versus exploration categorization of the adaptive processes used by firms is similar to our own categorization of IT investments. A CBI is aimed at exploiting the firm's current capabilities whereas a NII takes advantage of new opportunities and helps a firm adapt to potential threats. In general, regardless of the type of investment, a CBI typically is a higher priority than a NII. Thus, a key assumption in our work is that firms make CBIs before they make NIIs. In the next section we develop our hypotheses by building on this assumption.

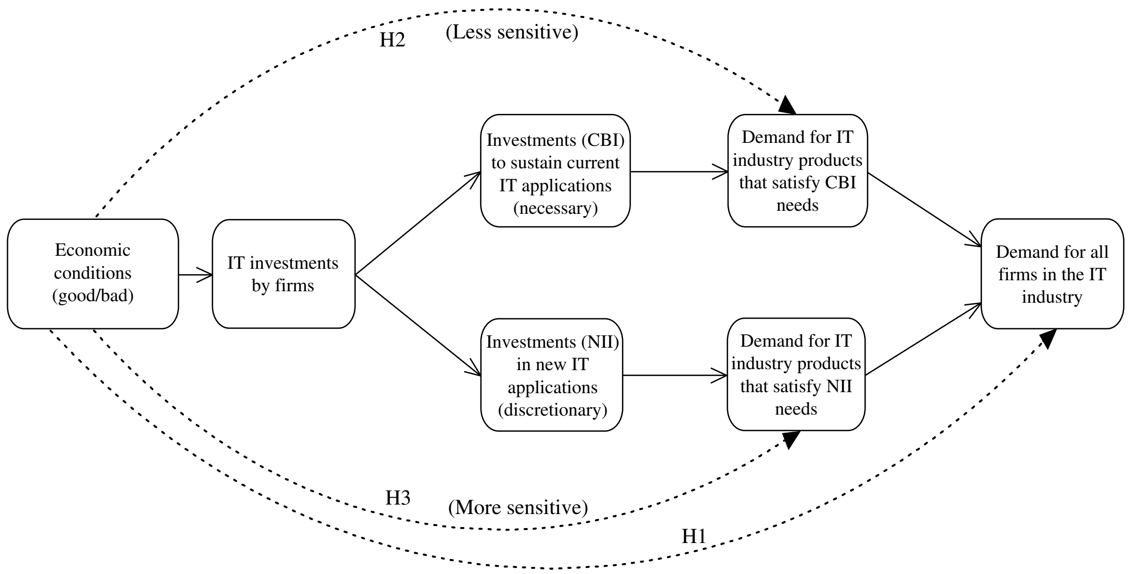
There is also anecdotal evidence that senior executives place a higher priority on CBI than NII. Christensen (2000) related a question from Andy Grove (then CEO of Intel™) during a presentation to Intel's senior executives. Andy Grove (sarcastically) asked, "Should we stop funding our current products that are very profitable and fund products that none of our customers currently want, that will lose money?" Christensen's presentation had suggested that Intel should invest in unproven technologies that, at the time, would not contribute to profits, because these investments could be very valuable down the road. This exchange between Christensen and Grove suggests that firms fund their current business activities before funding activities that could benefit them in the future.

2.3. Economic Conditions, IT Industry Demand, and Hypotheses

The demand for products is affected by economic conditions. In general, when economic conditions improve, demand increases, and vice versa. However, this general view is insufficiently nuanced; a change in economic conditions can affect products differently. Demand for products that are considered a necessity is affected less by changes in economic conditions than demand for discretionary products. For example, economic conditions affect consumer demand for medicine less than demand for furniture or vacations. The products of some industries are necessities for their customers, whereas others are discretionary.

[3] Our categorization of IT investments is conceptually similar to the categories described by Kobelsky et al. (2008). However, our definition of categories and the manner in which Kobelsky et al. (2008) operationalize their categories is different. Another view of the actions firms take that bears resemblance to ours is the exploration versus exploitation categorization in organizational learning (Benner and Tushman 2003). There are other categorizations such as Gartner's hype curve (Linden and Fenn 2003), and the stages in the product life cycle, that center on the technology itself; our focus is on the actions taken by firms.

Figure 1 A Model of IT Investments, Economic Conditions, and Their Impact on Firms in the IT Industry



Because a CBI is more of a necessity than a NII, changing economic conditions have a smaller impact on a CBI than a NII.

Today, all firms make CBIs to keep their current systems running. For a firm currently investing in new IT applications, the firm's IT budget includes both CBI and NII components. In the extreme case where all firms cease new IT application investments, all IT outlays are CBIs and IT spending will not be very sensitive to fluctuations in economic conditions. However, if firms continue investing in new IT applications, IT budgets will include both CBIs and NIIs, and IT spending will be more sensitive to economic conditions. As a result, changes in economic conditions affect the demand for products offered by IT firms differently when (1) new IT uses *are not* being developed and adopted, or (2) new IT uses *are* being developed and adopted. Under (1), IT firms' demand is a CBI for their customers. Under (2), IT firms' demand includes NIIs and CBIs for their customers. As a consequence, a change in economic conditions will affect demand for IT products more if firms continue to develop new IT uses than if firms stop doing so. Therefore, if investments in new IT uses are diminishing, we state our key hypothesis:

Hypothesis 1. Over time, demand for IT products has become less sensitive to changes in economic conditions.

Consider a firm in the IT industry that produces a single product. If the product is a NII for its customers, demand for the product will likely be greatly affected by changes in economic conditions. However, if the product is a CBI for its customers (e.g., the firm provides security protection for current systems), economic conditions will have relatively little effect on demand for the product. Therefore, we state the following hypotheses:

Hypothesis 2. Demand for IT products that are CBIs for their customers will be less sensitive to changes in economic conditions.

Hypothesis 3. Demand for IT products that are NIIs for their customers will be more sensitive to changes in economic conditions.

Hypotheses 2 and 3 determine whether our key assumption, that firms invest in CBIs before NIIs, is merited. Figure 1 depicts the relationships pertaining to Hypotheses 1, 2 and 3. We also summarize the assumptions, assertions, and conclusions to this point in Table 1.

Over the past 50 years, many different IT applications have been deployed by most firms in an industry (e.g., accounts receivable systems, office suites, etc.). IT applications that are eventually used by all competitors in a market become the price of entry to the market (Porter and Millar 1985).[4] The diffusion of successful IT product/process innovations has received considerable attention in the IS literature (Brancheau and Wetherbe 1990, Dewan et al. 2009,

[4] In the 1960s for example, IT was used to automate processing of simple transactions such as accounts receivable and payable, inventory control, etc. As IT costs decreased, competitors were able to implement similar applications and they became part of operations for all firms in the industry. Early on, those IT applications offered firms that processed large numbers of transactions opportunities to improve their performance. Over time, as competitors were also able to use IT to reduce these transaction processing costs; the differential advantages disappeared and the cost of automated transaction processing became the price of entry into most industries.

Table 1 **Summary of Assertions, Assumptions, and Rationale for Hypotheses**

1. There are two types of spending firms undertake: CBIs and NIIs.
2. A CBI is IT spending necessary to operate and maintain the applications that firms currently use to run their business.
3. A NII is spending on new initiatives that seek to take advantage of opportunities or respond to threats. This is spending aimed at implementing new IT applications that the firm expects to deploy in the future.
4. Firms generally make CBIs before they make NIIs (key assumption). In other words, a CBI is a necessity, and a NII is discretionary.
5. Discretionary spending is more sensitive to changes in economic conditions. Therefore, demand for products that are based on NII spending is more sensitive to changes in economic conditions than demand for products that are based on CBI spending.
6. WUCBI industries are non-IT industries that supply products that are widely-used inputs that primarily are CBIs for their customers (e.g., electricity and transportation industries).
7. If IT offers firms new opportunities to improve performance, IT expenditures include NII and CBI. If not, IT expenditures include only CBI.
8. Therefore, if IT offers firms new opportunities to improve performance, IT spending will be more sensitive to changes in economic conditions than spending on WUCBI industry products.
9. If IT does not offer firms new opportunities to improve performance, IT spending should become less sensitive to changes in economic conditions, eventually approaching the sensitivity of WUCBI industries.

Fichman and Kemerer 1999, Gurbaxani 1990, Iacovou et al. 1995, Loh and Venkatraman 1992).

The adoption of new IT initiatives by firms results in the demand for the IT firms that provide these products and services. Consider an IT innovation (e.g., an application software product) that eventually becomes widely adopted by firms. When the software is introduced, the demand for the software is a NII for early adopters. Once the early adopters have deployed the software, investments to keep the application running become CBIs for early adopters. As the innovation diffuses through a population of target firms, the demand for the product is a NII for the firms in the process of deploying the application. Thus, soon after the application is introduced, demand for the supplier includes some customers for whom the outlays are CBIs and others for whom they are NIIs, until the product has completely diffused through the population (reached saturation), at which point demand becomes a CBI for its customers. From a suppliers' perspective, the product life cycle encompasses the entire diffusion process of an innovation through the customer population. At one extreme, demand for the supplier is comprised entirely of NIIs for its customers. At the other extreme, demand is comprised entirely of CBIs for its customers. Between these extremes, the demand consists of both NIIs and CBIs. Thus, over time, the demand for IT products that eventually are widely adopted by firms transitions from being largely NIIs to being largely CBIs for customers.

When the demand for an IT firm's product is primarily comprised of NIIs for its customers, the firm's demand should be more sensitive to changes in economic conditions. Once the application has diffused through the population of target firms, continuing investments necessary to sustain the application are much less dependent on changes in economic conditions. Thus, the demand sensitivity to economic conditions should decrease over time as demand increasingly becomes a CBI for customers. Therefore, we state the following hypothesis.

Hypothesis 4. Over time, demand for IT products becomes less sensitive to changes in economic conditions as they transition from NIIs to CBIs.

Hypothesis 4 is one where we are interested in demand sensitivity over time as demand moves from being a NII to a CBI for customers. Hypothesis 4 is not represented in Figure 1 because we cannot depict temporal changes in the diagram. In the next three sections we describe the empirical study, including the method and data, the analysis, and the results.

3. Empirical Methodology

3.1. Method

We use financial market data and an event study approach to test these four hypotheses. Event studies are based upon the well-established paradigm in finance that asset prices in financial markets are affected by the arrival of new information. Over the past two decades, many IT-related studies have been based on this paradigm (e.g., Agrawal et al. 2006, Chatterjee et al. 2002, Dewan and Ren 2007, Dos Santos et al. 1993, Im et al. 2001, Raghu et al. 2008, Ranganathan and Brown 2006, Subramani and Walden 2001). In the financial literature, studies have investigated the "new information" effect on stocks (individual firms and industries), bonds, futures contracts, foreign-exchange rates, interest rates, and currency options, etc. (Nofsinger and Prucyk 2003). New information in financial studies can be firm-related decisions, or other events that affect asset prices. For example, one can study the effects of macroeconomic news on stock prices of firms in different industries (e.g., Hardouvelis 1987).

Past IT-related event studies have sought to determine whether the arrival of news about IT decisions by firms affects the firm's stock price. In this study, the new-information events are news releases of leading macroeconomic information. These news releases signal changes in economic conditions. We study the effects of such changes on the stock prices of groups of firms. The arrival of news about economic conditions causes investors to revise demand estimates for a firm's products, affecting the stock price of the firm.

Periodically, U.S. government agencies and other nonprofit agencies release a variety of information indicative of the state of the economy. There have been many studies on the reaction of stock markets to these news releases (Chatrath et al. 2006, Hardouvelis 1987, Jones et al. 1998). The change in stock price depends on the magnitude of the change in economic conditions (vis-à-vis the expected change) signaled by the news and the nature of the firm. It is well known that the stock price of a firm whose product demand is relatively invariant to economic conditions (e.g., those deemed necessities, such as food, freight, or utilities) is not greatly affected by a change in economic conditions, as are firms in industries whose products are deemed discretionary (e.g., building materials, amusement, engineering services; Kaplan and Peterson 1998).

Today, in addition to IT, there are industries that provide products/services (inputs) that most firms need to operate (e.g., electricity, freight); their products largely are CBIs for firms. We refer to non-IT industries that produce widely used inputs that primarily are *CBIs* for their customers as WUCBI industries. WUCBI industries supply inputs that do not provide the impetus for NIIs by firms. If investments in new IT applications are decreasing (i.e., IT investments are increasingly CBI), the volatility of stock prices of IT firms (as a whole) to changes in economic conditions will decrease and approach the stock price volatility of WUCBI industry firms.[5, 6]

3.2. Data

In this study, we (1) identify public firms in the IT industry and in WUCBI industries, (2) identify news sources that provide information signaling a change in economic conditions, (3) determine the price reaction for groups of firms to economic news, and (4) analyze the price reaction for groups of firms to changes in economic conditions to test our hypotheses.

We chose two benchmark industries to represent WUCBI industries: (1) utilities (*UT*) and (2) transportation and freight (*TF*). We chose these industries for the following reasons: (1) like the IT industry, the products of both industries are widely-used inputs by firms today; and (2) utilities and *TF* are infrastructure-providing industries, similar to IT. Besides, these WUCBI inputs did, at an early point in their development, offer NII opportunities for firms (Du Boff 1979, Hobsbawm 1975). As discussed later, we also chose two industries (rather than one) to increase the robustness of our results.

To identify publicly traded firms in the IT, utility, and *TF* industries over the relevant time period, we chose the six-digit North American Industry Classification System (NAICS) system (refined in 2007) over the four-digit Standard Industrial Classification (SIC) system (last updated in 1987). We found the SIC classification to be inadequate because our study spans a 28-year period during which time new technologies enabled new IT products, requiring the creation of new industry sectors to more accurately categorize firms. The utility and *TF* classifications are not very different between the two systems. Other IS researchers have used these third-party industry classification systems to identify firms belonging to an industry or sector (Bharadwaj et al. 1999, Dewan and Ren 2007).

At the six-digit NAICS level, eight utility sectors, 11 TF sectors, and 25 IT sectors appear in our data. We present sector-related details later (in Table A.1). We obtained daily stock price data for all firms in these sectors from the Center for Research in Security Prices (CRSP) database and identified the NAICS codes for individual firms from the Compustat database. The CRSP database only includes SIC codes, whereas the Compustat database contains both SIC and NAICS codes.

Both the U.S. government and independent agencies periodically release a variety of monetary and nonmonetary information (e.g., the unemployment rate, consumer price index, durable goods orders, producer price index, construction spending, etc.) that are indicative of economic conditions. We considered the leading macroeconomic announcements that have been used in a number of published studies in finance and economics literature (Chatrath et al. 2006, Ederington and Lee 1993, Hardouvelis 1987, Jones et al. 1998). For this set of macroeconomic news, we obtained announcement dates from 1980 through 2007. The events in this study are these macroeconomic news announcements. The announcement data is for a relatively comprehensive set of 16 different types of announcements. Summary information on the announcements for these news events is presented in Table A.2 (in the appendix).

In an event study, it is important to know when news reaches financial markets, because in an efficient market, the price response to new information is immediate (Ederington and Lee 1993). Most macroeconomic information is released by government and nonprofit organizations on a regular schedule.

[5] In our case, we are not concerned about the magnitude of the change in economic conditions because our interest lies in the *comparative* changes in stock prices of firms in the IT and WUCBI industries. The reason is that if the IT industry provides products that are primarily CBI for their customers, the volatility of stock prices of IT industry firms will approach the volatility in stock prices for firms in WUCBI industries.

[6] In our study, we do not directly observe individual firms' investment decisions. However, by observing the effects of changing economic conditions on the stock prices of relevant firms in the IT and WUCBI industries, we determine the extent to which firms are making investments in new IT applications.

Macroeconomic news is released monthly, bimonthly, or quarterly. These regularly scheduled news releases typically take place on specific days, at specific times. Most of these announcements are made just before U.S. financial markets open. A few announcements are made during the trading day (e.g., federal interest rates). No regularly scheduled macroeconomic news releases are made after U.S. financial markets close. The semistrong form of the efficient markets model, for which empirical evidence is strong, indicates that market prices fully reflect public information (Fama 1991). Hence, we use a one-day event window.[7] Note that there may be more than one event on the same day. In total, the 4,439 raw events occurred on 4,028 distinct trading days. Because we control for the type of news events in our analysis, having more than one event on the same day presents a problem, because it is not possible to separate the market reaction by event for those days on which multiple events occur. For such event days, we randomly assigned the date to one of the co-occurring events, because we are not interested in the impact of different types of events.

For each announcement, we computed a market-weighted price change for the announcement for each group (industry or sector, as needed for each hypothesis) on the announcement day. We computed the price volatility for group j on day t (R_{jt}) as follows:

$$R_{jt} = \frac{\sum_i (|P_{ijt} - P_{ij,\,t-1}| \times N_{ij,\,t-1})}{\sum_i (P_{ij,\,t-1} \times N_{ij,\,t-1})}, \tag{1}$$

where the price of the stock of firm i in group j at the end of trading day t is denoted by P_{ijt}; $N_{ij,\,t}$ is the number of shares outstanding for firm i, in group j, at the end of trading day t; R_{jt} is the market-weighted price change for the firms in group j on day t. We compute the absolute value of the change in price because we are interested in the magnitude of the change, not the direction. Note that the return is determined by the "new news" in the announcement. For example, if the market expects consumer spending to increase by 1%, an announcement that consumer spending increased by 0.8% may be interpreted by the market as negative (i.e., demand is likely to be less than the market expected). Bad news is likely to have a negative price effect, which is just as important for our purpose as good news having a positive price effect. Note also that we are interested in the *relative* price effect of the same news for IT firms as compared to firms in each of the two WUCBI industries. For Hypothesis 1 to be true, we should find that the price volatility of IT firms should be decreasing over time, when compared to the volatility of prices to utility or *TF* industry firms. Indeed, if IT investments are only CBIs, there should be little difference in the price response to macroeconomic news for IT firms and firms in the two WUCBI industries.

[7] In most event studies, the time of the event cannot be determined with precision because of the news source. For example, when the news source is a daily periodical, one cannot be sure whether the news affected prices on the day prior to the periodical's print date (i.e., it was released prior to the close of trading the previous day) or on the print date (it was released the day before, but after the markets closed). Hence, event studies that identify event dates from news in daily periodicals (e.g., *Wall Street Journal*), consider changes in market prices using a two-day event interval, including the day prior to the print date and the print date itself.

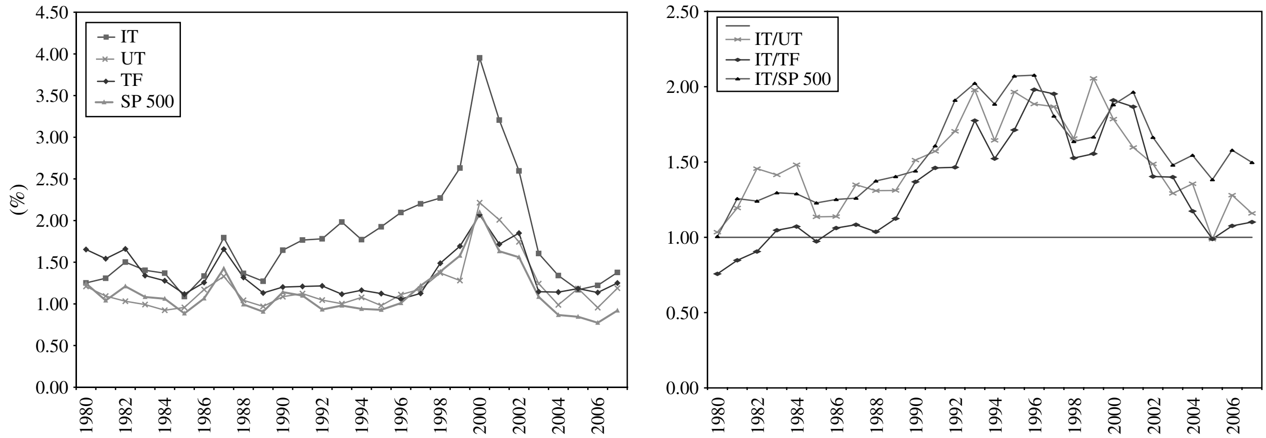
4. Analysis and Results

We used Equation (1) to compute the price change to new macroeconomic information for each of the three groups (IT, utility, and transportation and freight) for each year from 1980 through 2007. We also computed the ratio of the price change for IT firms to the two WUCBI industry firms. These ratios indicate the relative effects of new macroeconomic news for firms in the three industries. In addition, we computed the price volatility of the S&P 500 index (indicator of overall market volatility) to the same news as a benchmark and compared the ratio of the three industries to the S&P 500 index over time. If investments in new IT applications are decreasing, the volatility of IT firms to a change in economic conditions should be decreasing, relative to the S&P 500.

In Figure 2, we present these results in two graphs. In the top panel we show the volatility to economic news for the IT industry, the utility industry, the *TF* industry and the S&P 500 index over time. In the bottom panel, we plot volatility ratios: *IT*/utility, *IT*/*TF*, and *IT*/S&P 500 over time. The price volatility for IT firms to the news events range from 1.2% to 4.0% over the study period. The IT industry has consistently been above the volatility of the S&P 500 (i.e., market), whereas the volatility of the utility industry has mostly been below market volatility and the volatility of the *TF* industry has been slightly above market volatility. From the top panel, it is easy to see that the volatility of IT firms was abnormally high between 1995 and 2002, reaching a peak in 2000. This period roughly corresponds to the dot-com boom/bust period. From the bottom panel, we see that the IT-utility ratio was above one for the entire period; and IT-S&P 500 ratio was above one except for the year 1980, whereas the IT-*TF* ratio was above one after 1985.[8]

[8] The high volatility in prices of firms in the *TF* industry between 1980 and 1985 was likely due to the effects of the Motor Carrier Act of 1980, which deregulated the trucking industry. It was signed into law on July 1, 1980.

Figure 2 **Price Volatility of Industries Over Time**



Note. The top panel compares the price volatility of the IT industry, *UT*, *TF* industry and the benchmark S&P 500; the bottom panel compares the ratio of IT over *UT*, *TF*, and SP 500.

4.1. Evaluation of Hypothesis 1

Our initial analysis focuses on whether a significant difference exists between the volatility of IT firms, and WUCBI industry firms, and whether IT volatility is decreasing and approaching that of WUCBI industries. The three industries of interest include 44 sectors at the six-digit NAICS level (see Table A.2). We test the first hypothesis by estimating two models. We first estimate the following model:

$$\begin{aligned} Volatility_{ijt} = \beta_0 + \beta_1 \times UT + \beta_2 \times TF + \beta_3 \times Event_j \\ + \beta_4 \times Year_t + \beta_5 \times UT \times Year_t \\ + \beta_6 \times TF \times Year_t + \varepsilon_{ijt}, \end{aligned} \tag{2}$$

where $Volatility_{ijt}$ is the volatility of sector i, to event j in year t. We coded the IT industry as zero and created two dummy variables *UT* and *TF* for the utility and transportation and freight industries, respectively. Equation (2) specifies a simple fixed-effects model with interactions. We treated *year* as a continuous variable, coding the year as follows: zero for 1980, one for 1981, two for 1982, etc. The interaction terms between each WUCBI industry (*UT* and *TF*) and year tests whether the difference between IT and the relevant WUCBI industry changes over time. Estimation results for this model are reported in Table 2, under the Model 1.1 heading. Because of space and display size limitations, as well as our research interests, we do not display the fixed-effects coefficients for the variable *Event* (15 coefficients) in the table. First notice that the two main effects, the *UT* coefficient (-0.015) and the *TF* coefficient (-0.008), are negative and highly significant ($p < 0.001$). This suggests that over the entire period from 1980 to 2007, the IT industry (the benchmark industry under Model 1.1) was very different from both WUCBI industries. The interaction term between *UT* and *Year* is not significant ($p = 0.41$), indicating the trend over time is the same for both the IT and utility industries. However, the interaction between *TF* and *Year* is negative and significant (-0.0002), indicating that the difference is amplified over time. This is not a surprise because the *TF* industry had very high volatility prior to 1985 (see Figure 2). The net effect shows that, on average, IT industry volatility is 1.5% higher than the utility industry and 0.82% higher than the *TF* industry.

The model specified in Equation (2) implies a linear trend over time whereas the graphs in Figure 2 clearly indicate a nonlinear time effect. To address this problem, we added a quadratic term $Year^2$ to the model in Equation (2) to capture the nonlinear time effect. The results from estimation of the modified model are presented in Table 2, under the Model 1.2 heading. Adding a quadratic term for the year variable

Table 2 **Results for Hypothesis 1**

Variables	Model 1.1	Model 1.2
Intercept	0.024***	0.016***
UT_Dummy	−0.015***	−0.014***
TF_Dummy	−0.008***	−0.009***
Year	0.0002***	0.002***
Year^2	—	−0.00006***
UT_Dummy × *Year*	0.00003 (0.41)	−0.000 (0.98)
TF_Dummy × *Year*	−0.0002***	−0.0001***
Event	Included	Included
R-square	0.058	0.072
F-value	308.35***	364.96***
df	20	21
N	99,448	99,448

Note. Coefficients, with p-values in parentheses.
***Significant at 0.001.

improved R-square from 0.058 to 0.072.[9] The R-square values in financial studies of the market response to macroeconomic news are usually low (Chatrath et al. 2006, Gerlach 2007). The R-square rarely exceeds 0.10 in such studies. The new term $Year^2$ has a negative coefficient -0.00006 with a p-value less than 0.001. Introduction of the quadratic year term had no significant effects on the qualitative results, indicating that the volatility of prices of IT firms to changes in economic conditions is greater than that for the WUCBI firms. Hypothesis 1 is not supported; demand for IT products has not become less sensitive to changes in economic conditions. Investments in new IT applications are not diminishing.

4.2. Evaluation of Hypothesis 2

To test Hypothesis 2, we sought a group of IT firms (public) that provide primarily CBI products for firms. At a point in time, products offered by IT firms may be CBIs for some customers and NIIs for others. However, in looking at the NAICS classification of IT firms, we discovered a group of IT firms whose main products are primarily CBIs for their customers: firms that manage the computing facilities (MCF) of other firms (e.g., Electronic Data Systems, OAO Technology Solutions, Inc.). Demand for the services of these firms is primarily driven by their customers' need to keep current IT applications running smoothly.

IT firms that manage computing facilities are included in two NAICS codes, 541513 and 518210. The data indicates that the volatility of these MCF firms has been consistently lower than that of other IT firms' over time and is very close to the volatility of UT and TF firms. To test Hypothesis 2, we estimated the following model:

$$Volatility_{ijt} = \beta_0 + \beta_1 \times MCF + \beta_2 \times Event_j + \beta_3 \times Year_t + \beta_4 \times MCF \times Year_t + \varepsilon_{ijt}. \quad (3)$$

We created a dummy variable *MCF* that takes the value one for IT firms in MCF sectors and value zero for others. We also added an interaction term *MCF* × *Year* to examine the volatility of MCF firms over time. Note that only IT firms are included in the above estimation. The results are reported in the column Model 2.1 in Table 3. Firms in the MCF sector have a significantly lower volatility (coefficient -0.009 and $p < 0.001$) than other IT sectors. The $MCF \times Year_t$ term is also significant and negative, suggesting that over time the volatility of MCF firms has decreased relative to firms in the other IT sectors.

Table 3 Results for Hypothesis 2 (MCF Firms)

Variables	Model 2.1 (vs. IT)	Model 2.2 (vs. *UT*&*TF*)
Intercept	0.025***	0.015***
UT_Dummy	—	−0.007***
TF_Dummy	—	−0.0001 (0.81)
Year	0.002***	−0.000 (0.15)
UT_Dummy × *Year*	—	0.0003***
TF_Dummy × *Year*	—	0.000 (0.14)
MCF	−0.009***	—
MCF × *Year*	−0.0002***	—
Event	Included	Included
R-square	0.020	0.018
F-value	62.02***	45.15***
df	18	20
N	55,730	49,107

Note. Coefficients, with p-values in parentheses.
***Significant at 0.001.

We also compared the volatility of MCF firms to firms in the WUCBI industries. For this analysis, we used the model specified in Equation (2). However, in this case IT industry data includes only MCF firms, which were coded as zero, and UT and TF firms were coded as one. The estimation results are reported under Model 2.2 in Table 3. These results indicate that the volatility of MCF firms is significantly higher than that of *UT* (main effect of *UT* is -0.007), but the gap is shrinking (the interaction with year is positive with a coefficient of 0.0003). MCF firms are becoming more utility like. Interestingly, the volatility of MCF firms is not significantly different than that of *TF*, both for the main effect ($p = 0.81$) and the interaction effect with year ($p = 0.14$). Together, these results indicate that the demand for products offered by MCF sector firms is very similar to demand for products offered by WUCBI industry firms. The services offered by firms in these sectors are CBIs for their customers. Hypothesis 2, related to our key assumption, is supported; demand for IT products that are CBIs for their customers are less sensitive to changes in economic conditions. Firms invest in CBIs before NIIs. IT firms whose products are CBIs for their customers are less sensitive to changes in economic conditions than the IT industry as a whole and are similar to firms in WUCBI industries.

4.3. Evaluation of Hypothesis 3

To test Hypothesis 3, we sought a group of IT firms that provide primarily NII products for firms. Because the NAICS breakdown of firms does not have a category that meets these criteria, we had to use a different approach to obtain a relevant group of firms. For most public firms in the IT industry, it is difficult to categorize the firm as providing products that are

[9] Note that our unit of analysis is the sector (i.e., 44 sectors). If our data is aggregated to the industry level (i.e., IT, UT, and TF), our R-square increases from 0.058 to 0.494, without a material effect on the results. Results for this level of analysis are provided in the online appendix. In our case, aggregation at the sector level is appropriate. An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/isre.1110.0370.).

largely used by their customers to develop new IT applications (NII for customers). We were only able to identify one group of firms that met the above criteria, firms that provide products necessary for Radiofrequency identification (RFID) applications. Over the past few years, there has been an increased awareness that RFID-based applications may have become commercially viable (Lee and Ozalp 2007). To date, the demand for IT firms that provide products necessary for RFID applications is likely comprised largely of NIIs within firms trying to deploy RFID applications. Hence, the demand for these IT firms should be more sensitive to changes in economic conditions. Here, we analyze data for a group of firms that produce RFID products.

We identified a group of public firms whose main line of business was in RFID-based products, using the Hoover's company information database and the Compustat segment database. We excluded firms that produce RFID products, but for whom RFID is not their main line of business (e.g., Texas Instruments). The list of firms that met these criteria is reported in Table A.3 (in the appendix). The results of our analysis for this group of firms is found in the column titled Model 3.1 of Table 4. The results indicate that the volatility of stock prices for this group of firms is greater than that of the IT industry as a whole (excluding firms in the RFID group). The results in the columns titled Model 3.2 and Model 3.3 indicate that the volatility of stock prices for this group of firms is also much greater than the WUCBI industry firms and the S&P 500 firms, respectively. Hypothesis 3 is supported; the demand for IT firms that provide products that are necessary for new IT applications being deployed by firms is much more sensitive to changes in economic conditions than demand for firms whose products keep existing IT applications running smoothly.

4.4. Evaluation of Hypothesis 4

To test this hypothesis, we sought to determine whether IT applications transition from NIIs to CBIs over time. Consequently, we sought public IT firms that provide a product that has achieved success in the marketplace. For many years, firms have been purchasing and deploying enterprise resource planning (ERP), supply chain management (SCM), and customer relationship management (CRM) platform software systems from a number of vendors. Over time, more firms have adopted each of these systems, gradually increasing the number of firms for whom investments in these software systems are CBIs.

Table 4 **Results for Hypothesis 3 (RFID Product Producers)**

Variables	Model 3.1 (vs. other IT)	Model 3.2 (vs. WUCBI)	Model 3.3 (vs. SP 500)
Intercept	0.027***	0.012***	0.010***
RFID	0.008***	0.022***	0.027***
Event	Included	Included	Included
Year	0.0001***	0.0001***	0.00004 (0.39)
RFID × *Year*	−0.00008 (0.33)	−0.0004 (0.34)	0.0000 (0.95)
R-square	0.010	0.082	0.094
F-value	35.75***	245.24***	52.46
df	18	18	18
N	99,557	48,792	9,103

Notes. Coefficients, with p-values in parentheses.
***Sig. at 0.001.

Using the Hoover's company information database through the LexisNexis academy universe, we identified firms that are primarily in the business of providing CRM, ERP, and SCM platform software systems and for whom these products were their main sources of revenue. We cross validated the data with the Compustat segment database to determine whether a firm's main line of business is in one or more of these systems. This caused us to eliminate firms like Microsoft (SQL Server), IBM (DB2), and Infosys that sell products in one or more of these categories, but for whom these platform systems are not their main line of business. The firms in each category that met our criteria are shown in Table A.4 (in the appendix). This list of 43 firms is the most comprehensive set we could identify, encompassing those firms studied in Hendricks et al. (2007) and Dehning et al. (2007). The sample includes well-known firms in each category. ERP firms include the SAP, PeopleSoft, Oracle, and JD Edwards; the CRM firms include Siebel, Epiphany, and Salesforce; the SCM firms include i2 Technologies, Ariba, and JDA software.

Table A.4 indicates that many of these firms engage in multiple businesses, e.g., Oracle and SAP provide all three platform systems. It is important to note that no firm provides systems with only a combination of SCM and CRM capabilities (i.e., without ERP). All firms in our sample that provide more than one type of system are ERP vendors. Because ERP firms often also are in the CRM and/or SCM business, we separate ERP firms into three groups: ERP1 includes firms that provide only ERP systems; ERP2 includes firms that provide ERP systems and one of the other two types of systems (ERP and CRM, or ERP and SCM); ERP3 includes firms that provide all three platform software systems. We test Hypothesis 4 by estimating Equation (4):

$$\begin{aligned} &Volatility_{ijt} \\ &= \beta_0 + \beta_1 \times CRM + \beta_{21} \times ERP1 + \beta_{22} \times ERP2 \\ &\quad + \beta_{23} \times ERP3 + \beta_3 \times SCM + \beta_4 \times Event_j + \beta_5 \times Year_t \\ &\quad + \beta_6 \times CRM \times Year_t + \beta_{71} \times ERP1 \times Year_t \\ &\quad + \beta_{72} \times ERP2 \times Year_t + \beta_{73} \times ERP3 \times Year_t \\ &\quad + \beta_8 \times SCM \times Year_t + \varepsilon_{ijt}. \end{aligned} \tag{4}$$

Five dummy variables, *CRM*, *SCM*, *ERP*1, *ERP*2, and *ERP*3 represent firms in each category and their interactions with *year* are also included in Equation (4). We compute the volatility of returns for each of these five groups of firms to each news announcement using Equation (1). This data is then combined with the data for the WUCBI industries and used to estimate Equation (4). The results are presented in Table 5, under the Model 4.1 heading. With one exception, the results indicate that the stock prices of firms that provide these three types of applications are more volatile than firms in the WUCBI industries (the main effects, after factoring in the interaction effects, are positive and highly significant). However, over time, the gap is shrinking (the interaction terms with year are negative). The exception is the negative effect of *ERP*1 (after factoring the interaction effects), indicating that the firms that only provide ERP systems are very similar to WUCBI industry firms. However, ERP firms that have expanded into the other areas (CRM and SCM) are not like WUCBI industry firms. This suggests that most of the expenditures on ERP platform systems are now CBI, and many firms are still in the process of deploying CRM and SCM applications (expenditures are discretionary for many customers).

We also performed the same analysis (using Equation (4)) to compare the volatility of firms in each of these five groups to the S&P 500 Index. The results appear under the Model 4.2 heading. The conclusions are exactly the same as those reached from the results in column Model 4.1. Hypothesis 4 is supported.

5. Robustness Checks

In this section, we perform substantial additional analyses to ensure the robustness of our results.

Table 5 Results for Hypothesis 4 (Application Software Systems)

	Model 4.1 (vs. WUCBI)	Model 4.2 (vs. S&P 500)
Intercept	0.013***	0.010***
CRM	0.023***	0.026***
SCM	0.031***	0.035***
*ERP*1	−0.075***	−0.068**
*ERP*2 (+*CRM* or *SCM*)	0.077***	0.079***
*ERP*3 (+*CRM*+ *SCM*)	0.034***	0.037***
Event	Included	Included
Year	0.00008***	0.00005 (0.39)
CRM × *Year*	−0.004***	−0.0004***
SCM × *Year*	−0.0007***	−0.007***
*ERP*1 × Year	0.005***	0.005***
*ERP*2 × Year	−0.003***	−0.003***
*ERP*3 × Year	−0.0008***	−0.0008***
R-square	0.083	0.040
F-value	267.65***	68.48***
df	26	26
N	82,469	42,780

Note. Coefficients, with p-values in parentheses.
**Sig. at 0.01 and ***Sig. at 0.001.

5.1. Controlling for Firm-Specific Events

As noted earlier, firm-specific events are not particularly relevant to this study.[10] Here, we conduct a more formal analysis to show that our results are robust to a key firm-specific event. Many firm-specific events such as earnings announcements, mergers and acquisitions, management changes, etc. (Hotchkiss and Strickland 2003, Martin and McConnell 1991) are known to affect firm value (stock prices). One of the most important firm-specific news events is the quarterly earnings report required for publicly traded firms. In the typical quarterly report, firms also summarize the current state of their businesses, provide forecasts, and inform the markets about major changes within the business environment and organization. We reran our analysis with controls for quarterly earnings announcement news events. For each firm in our sample, we identified days on which each firm made quarterly earnings announcements from the quarterly Compustat (variable *rdqe*) database. Our calculation of volatility (using Equation (1)) uses the stock prices from two days, t and $t-1$. Because an earnings announcement may have affected prices on the announcement day or the next trading day (if the announcement was made after trading ended), for any firm that disclosed its quarterly earnings on a given day, we excluded price data for that firm for the announcement day and the next day. In total, 1,872 firms announced earnings 110,077 times over the 28 years on 6,315 distinct days.[11] The results reported in Table 6 are based on this new sample. All of the results are consistent with our earlier conclusions.

5.2. Leverage, Market Capital, and Market Growth

There is a good deal of financial literature on factors that affect stock price volatility (e.g., interest rates and financial leverage; Christie 1982). Most of this literature pertains to factors that affect the price volatility of individual firms. Most firm-specific factors are very unlikely to affect our results because we study the comparative impact on groups of firms, as opposed to

[10] Our unit of analysis is the sector. As a result, firm-specific events should have no material effects. Take firms' quarterly earnings announcements as an example. Our data contains 2,021 firms over 28 years. In each year, we expect to observe 8,084 such events, assuming each firm makes four such announcements annually. On average, there are about 250 trading days a year. Thus on a particular trading day prices for roughly 32 firms (=8,084/250) are affected by these announcements, representing 1.6% (=32/8,084) of the firms in the sample. It is unlikely that these announcements will affect the aggregated sector-level volatility systematically. Moreover, the size of our sample and the fact that firm-specific news events will affect prices in both directions makes it unlikely that our results will be affected by firm-specific news events.

[11] Note that many firms do not appear across the entire 28 years.

Table 6 Robustness Check Results After Matching with Nonevent Days, Controlling for Earnings Announcement and Three Control Variables

Variables	Model 1.1	Model 2.1 (vs. *IT*)	Model 2.2 vs. (*UT*&*TF*)
Intercept	0.025***	0.026***	0.021***
UT_Dummy	−0.012***	—	−0.008***
TF_Dummy	−0.007***	—	−0.004**
OG_Dummy	−0.005***		0.002***
Year	0.0003**	0.0001**	0.0004**
UT_Dummy × *Year*	−0.0003*	—	−0.0005***
TF_Dummy × *Year*	−0.0001 (0.53)	—	−0.0003***
OG_Dummy × *Year*	−0.0002**		−0.0005***
MCF	—	−0.003***	—
MCF × *Year*	—	−0.0003***	—
Leverage	−0.0003***	−0.0002**	−0.0002**
Firm_Size	−0.00002***	−0.00003***	−0.00003***
Growth_Rate	0.0001***	0.0001***	0.0002***
Event-CC	0.0005 (0.19)	0.0004 (0.52)	0.0008*
Event-CCI	0.0005 (0.15)	0.0003 (0.65)	0.0009**
Event-CPI	0.0010**	0.0020***	0.0000 (0.67)
Event-ES	0.0001 (0.84)	0.0004 (0.38)	−0.0003 (0.12)
Event-GDP	0.0004 (0.21)	0.0006 (0.22)	−0.0001 (0.32)
Event-NRC	0.0023***	0.003***	0.0014***
Event-IPCU	0.0002 (0.62)	0.0000 (0.71)	0.0001 (0.69)
Event-ITGS	0.00070*	0.0014*	0.0004*
Event-M3	0.0005*	0.0012*	−0.0002 (0.25)
Event-MCSS	0.0010**	0.0016**	0.0009**
Event-MTIS	0.0014***	0.0016***	0.0012***
Event-NAPM	0.0032***	0.0038***	0.0017***
Event-NRS	0.0012**	0.0018**	0.0006 (0)*
Event-PI	0.0014***	0.0014***	0.0001*
Event-PPI	0.0000 (0.95)	−0.0003 (0.44)	0.00003 (0.43)
Event-RS	0.0006*	0.0014**	0.0002**
R-square	0.090	0.074	0.018
F-value	433.12***	214.05***	54.66***
N and df	147,582 (26)	79,438 (22)	77,168 (26)

Note. Coefficients, with *p*-values in parentheses.
*Significant at 0.05; **significant at 0.01; ***significant at 0.001.

individual firms, and examined a very large number of events over a long period of time. However, we consider here leverage, market capital, and market growth potential as factors that may have a significant effect on price volatility of industry sectors because they could be different across our industry sectors.[12] We explain why these factors might affect our results and how we checked for their effects.

Financial leverage is known to affect price. Empirical evidence suggests that financial leverage statistically affects stock volatility, although the effect is small (Christie 1982, Schwert 1989). Leverage, typically measured as the debt-to-equity ratio of a firm, reflects the firm's capital and ownership structure. The composition of stakeholders of high-leveraged sectors may be very different than that of low-leveraged sectors, for which the main stakeholders tend to be stockholders. As a result, the same news may have a different effect on sectors with substantially different levels of financial leverage.

[12] In the online appendix we present the effects of three additional factors (dividends, physical assets, and price-to-earnings (PE) ratios). Qualitatively, none of these factors change our results.

We sought to determine whether the industry groups in our analysis were leveraged differently and whether our results were affected by differences in leverages across groups. We obtained yearly financial data from the Compustat database in order to determine leverage for each firm and aggregated the data to obtain a measure of leverage for each sector. We measured leverage as the debt-to-equity ratio (DER). Our data indicates that WUCBI firms in our sample tend to be more highly leveraged than IT firms. The average DER of utility, TF, and IT industries (in our data) is 3.96, 1.86, and 0.54, respectively. The water supply and irrigation system sector has the highest DER (6.9), whereas the software publishers sector has the lowest DER (0.14). We reran our analysis with leverage as a control variable to determine whether our results are different when we control for differences in leverage across groups. All the conclusions previously reached still hold. The coefficients, sign, and significance for the variables are consistent with the earlier results. (See Table 6, which also includes results for additional tests that are described in the subsections that follow.) The effects of the leverage variable are small and negative. For example, for our main results for Hypothesis 1, the *Leverage* coefficient is -0.0003 ($p < 0.001$), suggesting that firms with higher leverage tend to be less volatile but the magnitude is relatively small (0.03%). This is largely a result of the fact that WUCBI industries tend to have higher DER, yet a low volatility. The result is not consistent with the literature, which shows that at the firm level, an increase in leverage results in a small, but significant increase in volatility (Christie 1982). A recent paper, however, indicates that financial leverage generates little variation in stock return volatility at the market level but significant variation at the firm level (Aydemir et al. 2007). Because our analysis is conducted at a group level, the latter study may explain why our results differ from the results obtained at the firm level (Christie 1982).

The second factor we considered is firm size. It is well known that small cap stocks (i.e., smaller firms) are more volatile than large cap stocks (Fama and French 1992). It is possible that our results are due to differences in the market capitalization of firms in different sectors. Some sectors include only small cap firms, and others include many large cap firms. Hence we included market capitalization as a control variable. The results are reported in Table 6. The variable *Firm Size* under heading Model 1.1 in Table 6 shows a negative and significant impact, implying that larger-cap sectors do appear to be less volatile. However, controlling for market capitalization had no qualitative effect on our previous results.

The third factor considered is the stage of product diffusion. A new IT product that is in the early stages of its life cycle (before maturity) is still in the process of being deployed by some customers (new IT application). When the product reaches the maturity stage, it becomes a cost of doing business. However, identifying the stage of all the products for each industry sector considered in this study is virtually impossible. We used a proxy, the market growth rate of a sector, to approximate the stage of products in a sector. The sales growth of new products is expected to be greater than that of mature products. We thus used *Growth Rate* (overall sales of a sector in a year over the previous year's sales) as a control variable in our analysis. The results are reported in Table 6. Growth rate has a positive and significant impact, indicating that high-growth industries tend to be more volatile. After controlling for these three factors, our main results do not change qualitatively.[13]

5.3. Comparison with Nonevent Dates

Our analysis has focused on the relative volatility of stock prices of different groups on days when macroeconomic news was released. Here, to determine how our results would change, we look at the volatility of stock prices on days with and without macroeconomic events. Note that we have 4,028 days with events. From the pool of trading days without events (referred to as nonevent days), we randomly selected the same number of nonevent days to generate a balanced sample. We then combined the two samples (with and without events) and repeated the analysis for Hypotheses 1 and 2. All the results reported in Table 6 are based on this combined sample. All the main results remain the same (sign, significance, and magnitude). In Table 6, we also report the fixed effects for each of the macroeconomic news events. Because nonevent days are included (coded as zero) for the variable event, the interpretations of these fixed effects are straightforward—they represent the effect of these events when compared to the nonevent days. In the Model 1.1 column the significance varies across the 16 events, but all the significant events have positive signs, indicating that the volatility of firms in our sample is higher on event days; the volatility changes we observe are due to changing economic conditions.

5.4. Comparison with the Oil and Gas Industry

We compared the IT industry with two WUCBI industries—UT and TF—in this study. It should be noted that some firms in the utility industry group are regulated. The stock price volatility of regulated firms should be low because regulated firms are low risk; regulation in effect guarantees returns within a small range. Firms in the TF industry, on the other hand, are not regulated. By performing our comparisons (IT industry, MCF, etc.) to each of these two industries independently, we reduce the likelihood that our results are artifacts of our choice of WUCBI industry. This was one of the reasons that we chose to use two WUCBI industries.

Another commonly used input (though not as common an input as UT or TF) by firms is the product of firms in the Oil and Gas (OG) industry. We added the OG industry group in our analysis as another example of a WUCBI industry. The results are reported in Table 6 under the variable *OG*. Clearly the OG industry is more volatile than either UT or TF, but is still less sensitive to changes in the economic conditions than IT (the coefficient of *OG Dummy* is 0.002 and is significant under column Model 2.2). All the results are still consistent with our earlier conclusions.[14]

Finally, we repeated our analysis for Hypotheses 1 and 3 using SIC codes (instead of NAICS) to determine firm membership in the IT, utility, and transportation and freight industries. Our results for Hypotheses 1 and 3 do not change when SIC codes

[13] An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/isre.1110.0370.

[14] In the online appendix, we present comparative results for the biotech industry. The volatility of this industry is even higher than that of IT.

are used to categorize firms. We are unable to use SIC codes for Hypothesis 2 because the SIC system does not include clean categorizations of firms relevant to this hypothesis.

6. Summary and Conclusions

In this paper, we describe a study that sought to determine whether investments in new IT use is diminishing, specifically examining whether the opportunities to improve firm performance through new uses of IT are on the decline. The approach used to answer the question is based on the assumption that firms make investments necessary to keep their current business running before they make investments in new initiatives that will affect the future. Our empirical analysis is novel in that we employ an event study approach where the events are macroeconomic news releases and we assess the effects of these events on the value of groups of firms (i.e., a sector or industry). The longitudinal data used in this study is from 1980 to 2007 and includes firms in the IT, utilities, and transportation and freight industries. In addition, we also use data for the S&P 500 Index, when appropriate.

Our analysis indicates that firms continue to invest in new IT initiatives as they have in the past. Some earlier studies conducted at the firm level have indicated that firms do not retain much of the value generated by IT investments (Hitt and Brynjolfsson 1996, Prasad and Harker 1997). At a macrolevel, however, firms that make heavy use of IT perform better than firms that are light users (Brynjolfsson and Saunders 2010). Our results indicate that managers continue to find new ways to use IT to improve performance, which is essential for the economy as a whole because IT is a key driver of productivity (Brynjolfsson and Saunders 2010).

Clearly, NIIs by firms affect many individuals employed in IT-related professions. Whether these effects are positive or negative depends on an individual's perspective. Many IT-related jobs and entrepreneurship opportunities would diminish if firms discontinued NIIs. If NIIs dwindle, IT-related professions likely would cease growing, and might even contract. Thus, our results should be encouraging for people working in IT-related professions tightly related to NIIs. However, if the NII component of firms' IT investments continues to be large, changes in economic conditions will continue to have a large impact on IT employment opportunities. Demand for IT-related jobs will be highly volatile, which may not be received well by potential IT job seekers. NIIs also impact the perception of IT firms. A quote from a cover story in *Fortune* on whether growth in Google's core business is ending, captures the value of growth to an IT firm (Copeland and Weintraub 2010, p. 62): "... A growth company stock commands a premium price/earnings multiple based on its future potential that, in turn, helps it lure employees with stock options. Just as important, being a growth company affords employees and founders (and even shareholders) a huge psychological boost: You're driving the economy, you're changing the world."

Our analysis reveals that there are sectors of the IT industry that provide products/services similar to WUCBI industry firms. MCF firms provide services that typify *CBI*. The demand for MCF firms' products is not subject to wide stock price swings that are common for many firms in the IT industry. Furthermore, our analyses of IT firms that provide products that have been widely adopted (ERP systems) suggest that investments in these systems transition from being NIIs to being CBIs over time. Our results suggest that SCM and CRM platform systems have not yet reached the maturity stage, whereas ERP platform systems have arrived at such a point. Our analysis suggests that RFID investments primarily were NII for firms until 2007. Although Walmart went live with RFID (on pallets) in January 2005 (Songini 2006), item-level RFID deployment is just beginning (Wolverton 2010). However, Robert Carpenter, chief executive of the group that helped universal product codes (UPC) reach ubiquity, predicts a quick saturation of RFID, suggesting a rapid move of RFID from NII to CBI (Wolverton 2010). The fact that NIIs can become CBIs may bode well for some IT professionals during economic downturns. If the provision of these WUCBI-like IT services requires specialized skills that are not easily acquired by others, the jobs in these IT sectors will be relatively stable during economic downturns and upticks. There is additional evidence for this conclusion. According to Forrester Research, the relative stability of IT jobs in 2008 was primarily due to strong demand to meet day-to-day needs (Goldman 2009).

The finding that firms continue to discover new ways to use IT is important for IT firms. To maintain high growth, IT firms must sustain their efforts to provide new and innovative products and services. At the same time, IT firms need to improve their product offerings that support current IT use. Because NII applications eventually become CBIs over time, IT firms need to jointly and dynamically manage their product lines over time. The strategic allocation of the product portfolio of IT firms is an interesting topic for future research. Allocation decisions may have a direct impact on the operations of a firm, by, for example, affecting dividend decisions. The online appendix provides some evidence that the dividend level of IT firms is much lower than that of utility firms. The dividend level of IT firms was particularly low during the dot-com period, a period when IT firms' growth was expected to be particularly high.

Our data and analysis support the key assumption in this study, that firms make CBIs before they make

NIIs. During the dot-com boom period, it was widely perceived that there were tremendous opportunities for new IT applications; applications that could have a great impact on the future of firms in many industries. We know of no other period in the short history of IT when there was as widely-held perceptions of the potential for new IT applications. Consequently, during the dot-com period, it is likely that firms planned larger investments in new IT applications than at any other period in IT history. As a result, the volatility of prices of IT firms relative to WUCBI firms (to changes in economic conditions) should be much higher during the dot-com boom period than other periods. Figure 2 clearly shows that this is the case. Statistical analysis reported in an early version of this work indicates that the volatility of IT firms was significantly greater between 1995 and 2001 than in any other period in our sample (Dos Santos et al. 2008).

Over time, the IT industry has affected very different activities within a firm. Early on, IT was used to automate transaction processing within a firm. Later, IT helped improve decisions that required the use of information gleaned from a firm's transactions. Recently, IT has affected how firms interact with external constituents (customers, suppliers, etc.). The changing impact of IT on firm activities over time has largely been driven by the rapid decrease in IT prices and the opportunities that become available in a free market to exploit these price decreases. Although competitors may now be able to duplicate a firm's new IT application more easily, first movers are able to develop and deploy applications much more quickly. They also do so with greater success and lower risk. Thus, the return on investment (ROI) for new IT applications could be just as high as they were in the past. A recent paper concluded that the large returns on IT investments discovered in earlier empirical work may be explained by the fact that IT investments are riskier and therefore should (are expected to) provide larger returns (Dewan and Ren 2007). Our results, combined with the fact that firms increasingly buy rather than make the components necessary to deploy new IT applications, suggest that IT investment risks may have decreased over time. This raises an interesting empirical question: have IT investment risks changed over time?

This work is not without limitations. Our results are affected by how firms are categorized (i.e., which firms are IT firms). We chose to use the standard NAICS categorization for sectors. This general-purpose categorization may place firms in a category that knowledgeable observers may argue as belonging in a different category. For Hypothesis 1, our results hold when SIC codes are used to categorize firms. A more selective categorization of firms within each industry will likely provide even stronger evidence to refute Hypothesis 1.

In our study, we compare volatilities of two groups of firms. This approach will not work if the intent is to determine whether the volatility in a single sector has changed over time. However, the general approach used here can be adapted to allow such an investigation. In such a case, one will have to identify the "new news" in an event and adjust the observed volatility for the new news in the event.

We use a type of event study that has not been conducted in the IS area. Nor is this type of study conducted in finance or accounting (because they focus on different problems). However, a number of studies in finance determine how different types of assets react to macroeconomic news releases (we cite a few in the paper). Our empirical study is different. The logic of the theoretical model developed here could be used by researchers in other business disciplines to revisit questions of interest to them. For example, marketing academics are interested in early identification of a product's diffusion pattern. It is possible that stock price volatility may provide an earlier signal of product diffusion than current models do (which use sales data). Our analysis of suppliers of SCM, CRM, and ERP platform systems, and our analysis of RFID technology suppliers, suggests that this may be possible. Finance and accounting academics are interested in expert forecasts because many studies depend on them to determine news content. For example, expert forecasts of earnings are used to determine whether announced earnings are better/worse than the market expects (Ramnath et al. 2008). The logic of the theoretical model developed here suggests that expert forecasts will be less accurate for discretionary products than for necessities. If true, empirical studies in accounting and finance that use expert forecasts may need to be modified to account for this difference.

Our paper considers the supply side of the story. The demand side may be just as revealing. One could examine IT investment decisions made by individual firms over time. Harte-Hanks data on Fortune 1000 firms and IW-MPI census data provide potentially relevant data (on what IT expenditures and specific information systems firms purchased in a given year) for a select sample of firms. If this type of data is available on a larger scale, one may be able to determine how IT investment decisions are affected by changing economic conditions.

There is certainly a need for other studies to determine whether the opportunities that firms have to use IT to improve their performance are diminishing. One possibility is to do a more thorough examination of the effects of individual technologies (e.g., cloud computing) over time. Such a study could be conducted by examining the volatility of cloud computing providers to new news over time. For example, at the time of this research, cloud computing technology is still in an early stage and new IT use enabled by cloud computing is still a new initiative for most firms. However, once such a technology is adopted by a firm, the continuing investment (e.g., the usage-based subscription fee charged by Salesforce.com on its on-demand CRM systems) quickly turns into a CBI investment. Because of the nature of cloud computing, we conjecture that the transition from NII to CBI will be rapid, calling for a careful study of this technology sector in the near future. It is also possible that this question could be answered by gathering and analyzing different data (e.g., by surveying IT managers) or by using publicly available accounting and other data. We hope this paper will catalyze other research to address vital questions for IS professionals.

In this paper we present a model that links changes in economic conditions to differences in the demand for CBI and NII products and services, so that one can determine whether the new IT application opportunities for firms are decreasing. Our results indicate that, overall, the opportunities to use IT to improve firm performance are not diminishing.

Electronic Companion

An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/isre.1110.0370.

Appendixes

Table A.1 Price Volatility by Sector (Six-Digit NAICS Codes)

Row ID	Industry sectors	NAICS	Firm count	Data period	Volatility ratio
1	Software reproducing	334611	7	1986–2007	3.17
2	Electronic assembly manufacturing	334418	14	1980–1990	2.79
3	Semiconductor and related device manufacturing	334413	15	1984–2007	2.44
4	Broadcasting and wireless communication equipment	334220	14	1980–2007	2.28
5	Other electronic component manufacturing	334419	5	1980–2007	2.2
6	Other communications equipment manufacturing	334290	30	1981–2007	2.18
7	Internet service providers	518111	61	1991–2007	2.18
8	Computer terminal manufacturing	334113	19	1980–2003	2.13
9	Computer storage device manufacturing	334112	54	1980–2007	2.1
10	Computer and software stores	443120	5	1983–1990	2.01
11	Other telecommunications	517910	13	2000–2007	1.99
12	Custom computer programming services	541511	39	1980–2007	1.98
13	Telephone apparatus manufacturing	334210	76	1980–2007	1.98
14	Web search portals	518112	2	1999–2007	1.87
15	Bare printed circuit board manufacturing	334412	26	1980–2001	1.84
16	Computer systems design services	541512	258	1980–2007	1.84
17	Other computer peripheral equipment manufacturing	334119	188	1980–2007	1.78
18	Computer, peripheral, and software wholesalers	423430	14	1985–2007	1.77
19	Software publishers	511210	685	1980–2007	1.71
20	Electronic computer manufacturing	334111	70	1980–2007	1.68
21	Data processing services	514210	22	1980–2003	1.68
22	General freight trucking, local	484110	2	1997–2007	1.63
23	General freight trucking, long distance, truckless	484122	13	1980–2007	1.59
24	General freight trucking, long distance, truckload	484121	56	1980–2007	1.56
25	Other electric power generation	221119	14	1980–2007	1.55
26	Other computer related services	541519	40	1980–2007	1.46
27	Deep sea freight transportation	483111	44	1980–2008	1.45
28	Short-line railroad	482112	1	1992–2007	1.31
29	Inland water freight transportation	483211	3	1980–2008	1.27
30	Computer facilities management services	541513	3	1980–2007	1.2
31	Costal & Great Lakes transportation	483113	5	1980–2008	1.2
32	Cellular and other wireless telecommunications	517212	19	1980–2007	1.15
33	Data processing, hosting, and related services	518210	23	1980–2007	1.13
34	Line-haul railroad	482111	35	1980–2008	1.12
35	Pipeline transportation of gas	486210	42	1980–2009	1.06
36	Fossil fuel electric power generation	221112	2	2000–2007	0.94
37	Steam and air-conditioning supply	221330	2	1983–1990	0.92
38	Water supply and irrigation systems	221310	23	1980–2007	0.91
39	Pipeline transportation of oil	486110	2	2002–2007	0.88
40	Pipeline transportation of refined petroleum	486910	8	1985–2007	0.82
41	Natural gas distribution	221210	62	1980–2007	0.81
42	Hydroelectric power generation	221111	1	1980–2007	0.72
43	Sewage treatment facilities	221320	1	1980–1990	0.7
44	Electric power distribution	221122	3	1980–2007	0.62

Table A.2 Summary Information of the News Events

Event symbol	Event type	No. of event	Frequency	Starting date	Source
CCI	Consumer confidence index	338	Monthly	1/29/1980	The Conference Board
CPI	Consumer price index	344	Monthly	1/25/1980	U.S. Department of Labor: Bureau of Labor Statistics
ES	Employment situation	342	Monthly	1/11/1980	U.S. Department of Labor: Bureau of Labor Statistics
CC	G.19 consumer credit	139	Monthly	12/6/1996	Board of Governors of the Federal Reserve System
GDP	Gross domestic product	360	Monthly	1/18/1980	U.S. Department of Commerce: Bureau of Economic Analysis
IPCU	Industrial production and capacity utilization	353	Monthly	1/16/1980	Board of Governors of the Federal Reserve System
ITGS	International trade in goods and services	138	Monthly	1/17/1997	U.S. Department of Commerce: Bureau of Economic Analysis
NAPM	Manufacturing NAPM/ISM report on business	145	Monthly	3/3/1997	Institute for Supply Management
M3	Manufacturer’s shipments, inventories, and orders (M3) survey	440	Half Month	2/27/1990	U.S. Department of Commerce: Census Bureau
MTIS	Manufacturing and trade inventories and sales	136	Monthly	11/15/1996	U.S. Department of Commerce: Census Bureau
MCSS	Michigan’s Consumer Sentiment Survey	116	Monthly	7/31/1998	Survey Research Center at U. of Michigan
NRC	New residential construction	438	Monthly	1/17/1980	U.S. Department of Commerce: Census Bureau
NRS	New residential sales	106	Monthly	7/30/1999	U.S. Department of Commerce: Census Bureau
PI	Personal income	346	Monthly	1/17/1980	U.S. Department of Commerce: Bureau of Economic Analysis
PPI	Producer price index	346	Monthly	1/11/1980	U.S. Department of Labor: Bureau of Labor Statistics
RS	Retail sales	352	Monthly	1/11/1980	U.S. Department of Commerce: Census Bureau

Table A.3 RFID Firms in the Sample

Company name	Ticker
Alanco Technologies, Inc.	ALAN
B.O.S. Better On-line Solutions Ltd.	BOSC
Checkpoint Systems, Inc.	CKP
Digital Angel Corporation	DIGA
I.D. Systems, Inc.	IDSY
InfoLogix, Inc.	IFLG
Innovative Card Technologies, Inc.	INVC
Intermec, Inc.	IN
VeriChip Corporation	CHIP
Scansource, Inc.	SCSC
VUANCE Ltd.	VUNC
Zebra Technologies Corp	ZBRA

Table A.4 CRM, ERP, and SCM Firms in the Sample

Company Name	TICKER	SCM	CRM	ERP
Acxiom Corporation	ACXM		X	
Amdocs Limited	DOX		X	
American Management Systems	AMSY			X
American Software, Inc.	AMSWA	X		
Ariba, Inc.	ARBA	X		
AsiaInfo Holdings, Inc.	ASIA		X	X
Ask Computer Systems Inc.	ASKI			X
Astea International Inc.	ATEA		X	
Baan	BAANF			X
CDC Corporation	CHINA	X	X	X
Chordiant Software, Inc.	CHRD		X	
Deltek, Inc.	PROJ			X
DemandTec, Inc.	DMAN	X		
e-Future Information Technology Inc.	EFUT	X		

Table A.4 (Cont’d.)

Company Name	TICKER	SCM	CRM	ERP
eLoyalty Corporation	ELOY		X	
Epicor Software Corporation	EPIC	X	X	X
Epiphany, Inc	EPNY		X	
ePlus inc.	PLUS	X		
i2 Technologies, Inc.	ITWO	X		
Jack Henry & Associates, Inc.	JKHY		X	
JD Edwards	JDEC	X	X	X
JDA Software Group, Inc.	JDAS	X		
Lawson Software, Inc.	LWSN	X	X	X
Logility, Inc.	LGTY	X		
Manhattan Associates, Inc.	MANH	X		
Manugistics Group Inc.	MANU	X		
Market Leader, Inc.	LEDR		X	
ModusLink Global Solutions, Inc.	MLNK	X		
NetSuite Inc.	N		X	X
Omnicell, Inc.	OMCL	X		
Oracle Corporation	ORCL	X	X	X
PeopleSoft, Inc.	PSFT	X	X	X
Prescient Applied Intelligence Inc.	PPID	X		
QAD Inc.	QADI	X	X	X
RightNow Technologies, Inc.	RNOW		X	
Ross Systems, Inc.	ROSS	X		X
S1 Corporation	SONE		X	
salesforce.com, Inc.	CRM		X	
SAP Aktiengesellschaft	SAP	X	X	X
Siebel Systems, Inc.	SEBL		X	
SSA Global Technologies	SSAG	X	X	X
The Descartes Systems Group Inc.	DSGX	X		
XATA Corporation	XATA	X		

Note. We use “X” to indicate that the company has a substantial line of business (at least 10% of its application software revenue) in the column category.

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