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# PATTERNS OF COMOVEMENT: THE ROLE OF INFORMATION TECHNOLOGY IN THE U.S. ECONOMY

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Patterns of Comovement: The Role of Information Technology in the U.S. Economy
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**ABSTRACT**

Firm-specific variation in stock returns and fundamental performance measures is significantly higher in industries that have a history of more investment in information technology (IT). We hypothesise that IT is associated with creative destruction or product differentiation, either of which can widen the performance difference between winner and loser firms. Thus, economy-level volatility can fall while firm-level volatility rises because firm-specific volatility cancels out in the aggregate. Our results are consistent with rising firm-specific variation in US stocks reflecting a rising pace of creative destruction; and with greater firm-specific variation in richer and faster growing countries reflecting more intensive creative destruction in those economies, though other explanations are probably valid as well.

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*"A wave of innovation across a broad range of technologies, combined with considerable deregulation and a further lowering of barriers to trade, fostered a pronounced expansion of competition and creative destruction. The result through the 1990s of all this seeming-heightened instability for individual businesses, somewhat surprisingly, was an apparent reduction in the volatility of output and in the frequency and amplitude of business cycles for the macroeconomy."*

*Alan Greenspan, Speech on Economic Volatility, 2002.*

*"The fundamental impulse that keeps the capital engine in motion comes from the new consumers' goods, the new methods of production and transportation, the new markets...[The process] incessantly revolutionizes from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact of capitalism."*

*Schumpeter, on the Creative Destruction, 1942.*

## 1. Introduction

During the past few decades, aggregate volatility in the U.S. economy fell significantly (Blanchard and Simon, 2001). In particular, McConnell and Perez-Quiros (2000) find a structural break in U.S. GDP volatility around 1984. Volatilities of other macroeconomic variables, such as inflation and unemployment, exhibit similar patterns (Stock and Watson, 2002).[5]

In contrast, the volatilities of firm-level performance measures rose sharply over the same period. Figure 1 shows this intriguing divergence between macro (aggregate-level) and micro (firm-level) volatilities. Figure 1 contrasts the aggregate volatilities of sales growth, return on assets (ROA), and the stock market return with the average volatilities of firm-level sales growth rates, ROAs, and stock returns.[6] All the firm-level volatilities trend upward from 1971 through 2000, while the aggregate volatilities trend down or hold steady.

Lower aggregate volatility is clearly not due to lower firm-level volatility. The divergence between macro and micro volatilities implies that correlations among firms declined over time, both in real (sales growth rate and ROA) and financial (stock return) terms. In other words, firm-specific (idiosyncratic) volatilities rose faster than industry- or economy-wide (systematic) volatilities over the sample period.[7]

In this paper, we propose that creative destruction associated with the rapid diffusion of Information Technology (IT) plays a major role in the aforementioned divergence. Creative destruction, Schumpeter's (1942) theory that economic growth arises from creative firms adopting new technology, thereby destroying stagnant firms, necessarily has winners and losers. We propose that the incorporation of IT by existing

[5] Blanchard and Simon (2001) and Stock and Watson (2003) also show that GDP volatilities declined in other major advanced countries as well. In addition, Stock and Watson (2003) find that business cycles in G7 countries have not become more synchronized despite large increases in trade and openness.
[6] Details on construction of the three variables and calculation of volatilities are explained in Section 4.
[7] Morck *et al.* (2000) and Campbell *et al.* (2001) report increased firm-specific volatility in U.S. stock return over the latter decades of the twentieth century.

industries induces a tremor of creative destruction, and that this explains both increased firm-level volatility and increased heterogeneity among firms.

We propose that IT is a General Purpose Technology (GPT), like electrification in the early twentieth century. Helpman and Trajtenberg (1998) define a GPT as a technology that transforms the way firms conduct business in general. Bresnahan *et al.* (2002) show successful adopters of a GPT to possess complementary inputs, notably skilled labor and appropriate organizational forms. In a similar vein, Hayek (1941) stresses managerial foresight as a complementary input. However, the distribution of these complements is not uniform across firms. Thus, some firms succeed with IT; others fail. This increases firm-level volatility and heterogeneity as winners and losers diverge within industries.

In the process of creative destruction, IT may further increase heterogeneity, even among successful adopters, by permitting more product differentiation in intangible aspects of output such as better customer services. Thus, even though firms in the same industry may produce similar tangible products, they could attract diverse pools of consumers, generating yet more heterogeneous performance among firms within the industry.[8]

Overall, IT plausibly makes firm performance more volatile and heterogeneous, raising firm-specific volatility.

Panel A of Figure 2 shows IT investment (computers, software, and related assets) rising steadily from about 3% of total investment in the early 1970s to 17% by 2000. In 2000, U.S. firms invested \$273 billion in IT – almost 3% of GDP.[9, 10] Panel B shows that, despite declining somewhat over time, substantial cross-industry variation in IT intensity (the ratio of IT capital to total capital) persists in 2000.[11] This variation provides a natural cross-sectional testing ground for studying the effects of IT assets on the volatilities of various performance measures.

We find that industries with higher IT intensity exhibit larger firm-specific volatility in a range of performance measures. This finding is robust to controlling other industry characteristics that might affect volatility, such as research and development (R&D), average firm age, industry price competition, physical investment, foreign exposure, distribution of firm size, liquidity, book to market ratio and firm diversification.[12] We also find that the growth rate of idiosyncratic volatility is higher in more IT intensive industries.

This finding provides several new insights into stock market volatility, the nature and consequences of IT investment, and economic growth.

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[8] Section 2 fully discusses the two channels how IT could affect firm-specific volatility.

[9] U.S. firms invested \$180 billion in Research and Development (R&D), excluding federally funded R&D, or about the half of their IT investment.

[10] Time-series patterns of IT and volatility suggest a possible relationship between the two variables. However, since both exhibit strong time trends (IT intensity in many industries contains a unit root), they are subject to well-known inference problems. Thus, our paper mainly focuses on the cross-sectional effects of IT investment on volatility.

[11] Comparing diffusion patterns of IT and electrification across industries, Jovanovic and Rousseau (2003) show that IT has diffused more slowly than electrification. In the period of 1960-2001, cross-industry variation of IT has declined, but is still substantial – even in the latter part of the period. Details on the distribution of IT investment across industries are discussed in Section 3.

[12] Section 3 discusses in detail the different characteristics between IT and R&D.

First, our study identifies an underlying factor behind the recent increase in firm-specific volatility in the U.S. stock market found in Morck *et al.* (2000) and Campbell *et al.* (2001). Schumpeter (1912) argues that innovation is a process of creative destruction, whereby creative new firms bring innovations to market, destroying established old firms. Higher firm-specific stock return volatility indicates a more extreme divergence of winners from losers, and so might be a sign of intensifying creative destruction in the U.S. economy.

This builds on other recent findings regarding firm-specific returns volatility. For example, Wei and Zhang (2004) show that changes in stock return volatility closely track changes in earnings volatility. This suggests that real economic factors cannot be ignored in explaining the rising firm-specific returns variance in U.S. stocks. We take this argument a step further by exploring and testing a detailed economic explanation of why real firm performance measures exhibit greater firm-specific volatility.

Our explanation also accords with other recent findings relating firm-specific returns volatility to a variety of other important economic variables. Morck *et al.* (2000) and Durnev *et al.* (2004) find higher firm-specific volatility related to higher real GDP *per capita* and faster economic growth, respectively. This is consistent with more intensive creative destruction underlying faster and more sustained economic growth, as in Schumpeter (1912) and the *new endogenous growth theory* summarized in e.g. Aghion and Howitt (1998).

Greater firm-specific volatility is related to general measures of financial development (Wurgler, 2000) and a variety of variables measuring more specific dimensions of financial development. These include reduced arbitrage costs (Bris *et al*., 2004); greater transparency (Bushman *et al*., 2002; Durnev *et al.*, 2004; and Jin and Myers, 2004); and more open capital markets (Li *et al.*, 2004). King and Levine (1993) demonstrate a highly significant relationship between a county's financial development and its economic growth, consistent with Schumpeter's (1912) thesis that well-functioning financial institutions and markets are necessary to finance the rapid growth of innovative firms. Higher firm-specific volatility might thus occur in countries with better financial institutions and markets because these permit faster creative destruction.

This insight in no way precludes other theories of firm-specific returns variation. For example, Jin and Myers (2004) link greater firm-specific fundamentals and returns variation to better institutions to prevent corporate insiders and officials from confiscating firm-specific abnormal profits, and present convincing evidence of such a link. This view is also consistent with much other work, and ought to be regarded as a complement to ours, rather than an alternative theory. In fact, our paper might be considered a special case of their framework, in which greater transparency limits insider malfeasance, allowing better financing terms for honest innovators, and hence faster creative destruction.

A second insight is that IT researchers might consider second moments. The existing IT literature focuses on first moments – the growth rates of individual firms, industries, and economies. Stiroh (2002) shows that innovation associated with IT can increase the growth rate of an industry.[13] Using a growth accounting framework, Oliner

[13] The relationship between IT and economic performance is somewhat sensitive to the sample period. For example, Stiroh (2002) and Brynjolfsson and Hitt (2003) find a significant positive IT effect using data after the late 1980s. However, Loveman (1994) and Stiroh (1998) fail to find any significant relationship in

and Sichel (2000) and Jorgenson (2001) show that the growth in IT capital stock accounts for over half the rise in U.S. productivity growth in the late 1990s. Brynjolfsson and Hitt (2003) find similar results at the firm-level. Since IT intensity is positively associated with firm-specific volatility, highly innovative industries could generally have both low aggregate volatility and high firm-specific volatility.[14] This is because the purely firm-specific component of volatility is diversified away at the industry or economy level.

A third insight undermines theories that explain macro volatility with micro volatility. Kahn *et al.* (2001) explain declines in aggregate volatility with IT investment, arguing that better inventory management, production planning, and demand forecasting reduce aggregate volatility. However, this implies declining firm-level volatility too, which Figure 1 belies. A variant of the Keynesian *fallacy of composition* applies. Aggregate variation is not the simple sum of firm variations.

Fourth, our findings also illuminate the relationship between volatility and macroeconomic performance. Morck *et al.* (2000), Jin and Myers (2004), and others find higher firm-specific stock return volatility in richer countries. Durnev *et al.* (2004) find higher firm-specific stock return volatility correlated with faster GDP and productivity growth across countries. He *et al.* (2004) link faster GDP and productivity growth to increased turnover in the lists of countries' leading firms. On surface, these results seem to contradict Ramey and Ramey (1995), who find countries with higher aggregate volatility to grow slower. Ramey and Ramey interpret their finding as consistent with the literatures on investment under uncertainty, such as Pindyck (1991), wherein increased uncertainty depresses corporate investment. However, our findings suggest low aggregate volatility can coincide with high firm-level volatility because creative destruction induces firm-specific volatility, which averages out in aggregate measures. In an economic growth model with creative destruction, Aghion and Howitt (1992) argue that both the average growth rate and the variance of the growth rate are increasing functions of the size of innovations as well as the size of the skilled labor force and the productivity of research.

The paper is structured as follows. Section 2 examines how IT can affect firm-level volatilities. Section 3 describes the construction and characteristics of our industry-level IT variable. Section 4 examines the characteristics of firm-level volatility, and the changes in correlation patterns of sales growth rates, ROAs, and stock returns. Section 5 explains our decomposition of total volatility into firm-specific and systematic components. Section 6 discusses regression results, and Section 7 concludes.

## 2. Information Technology, Volatility, and Alternative Hypotheses

Section 2.1 describes two channels through which IT might affect firm-specific volatility. Section 2.2 considers other relevant industry characteristics that might affect firm-specific volatility.

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the earlier period. Evidence of a time varying effect of IT is also consistent with the GPT theory, suggesting that the gains from new GTPs are delayed for some time. This delayed effect of IT is often called the IT productivity paradox. See Helpman and Trajtenberg (1998) for a theoretical explanation.

[14] In a similar spirit, Dunne *et al*. (2004) argue that the increasing dispersion of wages and productivity at the plant-level reflects the differential adoption of new technology, in particular, computer investment.

### *2.1 IT and Volatility*

Information Technology is often considered an example of *general purpose technology* (GPT), which Helpman and Trajtenberg (1998) and Jovanovic and Rousseau (2003), and others define as a technology that transforms the way firms conduct business.[15] Usually, the introduction of a new GPT is somewhat exogenous and episodic, but firms must adopt it to survive in the long run. As a GPT, IT spreads to firms in all sectors, permitting innovation in *new processes and product*s (Bresnahan and Trajtenberg, 1995). This section reviews two important channels through which IT causes firms to be more volatile and heterogeneous; that is, to exhibit greater firm-specific variation.

*First channel: IT increases firm-level heterogeneity by permitting improvements in new production processes with different values for different firms.*

Like most GPTs, IT investment benefits different firms differently. Successful adoption of IT requires complementary assets – Bresnahan *et al.* (2002) and Brynjolfsson *et al.* (2003) stress skilled workers and firm organization, while Hayek (1941) focuses on managerial foresight. Firms with more complementary assets gain the most from IT.[16] These complementary assets mean that a firm's *effective IT capital stock* could differ from its reported value. Since these complementary assets are predominantly firm-specific, production processes should exhibit more heterogeneity as IT capital stock rises.

In a similar spirit to this explanation, Hobijn and Jovanovic (2001) also examine the *ex-post* effect of the introduction of IT. They emphasize the difference in the relative benefits of IT between incumbents (old firms) and entrants (new firms). Their intuition is that IT may not be fully functional in old firms because the resources used to run old technology are not fully transferable to new technology. Therefore, new firms without old technology benefit more from IT. In support of their theory, they find that industries with higher IT intensity experience larger decreases in aggregate market value when a new IT arrives.[17] If older firms are larger, this implies that heterogeneity between small and large firms should increase after a new IT arrives. Consistent with this line of argument, we find that correlations between large and small firm performance declines over time in the U.S.[18] In addition, we also find that correlations between large firms decrease as well. Thus, heterogeneous benefits of IT are evident not only between small and large firms, but between firms in general.

*Second channel: IT increases firm-level heterogeneity by increasing the importance of intangible aspects of output.*

IT lets firms develop new products and improve intangible aspects of existing

[15] Other examples of GPTs are steam engine, the factory system, and electricity. In particular, Jovanovic and Rousseau (2003) contrast characteristics of two GPTs: IT and electricity.

[16] For example, Brynjolfsson (2002) *et al.* find that firms with higher levels of *both* computer and organizational investment have higher stock market valuations than firms that invest heavily in only one of the two.

[17] A similar argument is also found in Laitner and Stolyarov (2003), who suggest that new information technologies render old knowledge and physical capital obsolete and thereby reducing the market value of physical capital.

[18] Correlation patterns are discussed in Section 4.

ones, thus deepening the uniqueness of products made by successful IT adopters. If this deeper product differentiation reduces the substitutability of different firms' products (Syverson, 2004), firm-specific volatility could rise as one firm's product is revealed to be superior or attractive to certain groups of customers.

Surprisingly, given IT's technological roots, its major benefits to firms seem to involve product differentiation of this sort.[19] Brynjolfsson and Hitt (2003) survey Fortune 500 information system managers in 1997 and report the top five reasons for IT investment: 1) improving customer service, 2) targeting new customers, 3) improving quality, 4) reducing total cost, and 5) improving timeliness. Four reflect intangible aspects of output. Likewise, using data on the U.S. postal service, Mukhopadhyay *et al.* (1997) report that IT raises the quality of output measured by the timeliness of mail processing. Athey and Stern (2002) also find that IT decreases response times of emergency response systems and improves healthcare outcomes.

A National Science Foundation (NSF) survey (2004) asks the managers of about two thousand firms if IT has small, moderate, or great effect on cost reduction and quality improvement. About 80% of respondents replied that IT has at least a moderate effect (about 40% for a great effect).[20]

### *2.2 Volatility and Alternative Hypotheses*

This section introduces other industry characteristics that might affect cross-industry variation in firm-specific volatility. Details about the construction of each corresponding control variable are in the appendix.

*Corporate Demography*

Smaller and younger firms might have greater dispersion in performance. An industry consisting of relatively young firms might thus exhibit greater firm-specific volatility.[21] As a proxy for the average age of firms in an industry, we use two measures. Our first age measure is calculated using the listing year from CRSP monthly data. The second is the average age of the firms' capital assets, measured as in Hall (1990). The two measures are highly correlated, and generate similar results in our multiple regressions.

*Price Competition*

The degree of price competition in an industry can affect firm-level performance variation. Intense price competition means that a negative firm-specific shock might cause bankruptcy, while a positive shock might provide an important competitive edge over rival firms.[22] Intense price competition might thus amplify firm-specific volatility.[23]

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[19] This is a very unique nature of IT as a GPT. For example, electricity does not deepen the uniqueness of products.

[20] Managers of both small and large firms stress the importance of IT in their responses. There is little variation in answers to the two questions across firms with different sizes (e.g., less than $5 million, 5-10M, 10-25M, 25-50M, and 50M or more) and across industries (e.g., manufacturing versus non-manufacturing). In this regard, IT differs from R&D, which is typically concentrated in relatively large firms in manufacturing. Other differences emerge in Section 3.2.

[21] For recent evidence, see Pastor and Veronesi (2003).

[22] Philippon (2003) develops a model in this spirit.

[23] International competition can also increase firm-level volatility (Comin and Mulani, 2003, Li *et al.*, 2004). Since international trade is concentrated in tradable goods industries (mainly manufacturing), this

Thus, we must ensure that any relationship between IT and firm-specific volatility is not merely an artefact of heterogeneity in price competition across industries.[24] To measure the intensity of price competition in each industry, we calculate Herfindahl-Hirschman Index (HHI).

*Distribution of Firm Size*
The distribution of firm size may reflect pre-existing heterogeneity among firms, which could affect volatility.[25] We calculate the standard deviation of the logarithm of firm market capitalizations, sales, and total assets to measure the dispersion in firm size for each industry.

*Conventional Investment*
Investment in conventional capital assets might also increase firm-level performance variation by increasing uncertainty about firms' future cash-flows. Or, increased volatility might discourage firms from making capital expenditures.[26] Which of these two effects dominates in a cross-sectional analysis is an empirical question. Regardless, we include the investment rate in non-IT capital as an additional control variable.

*Other Intangible Investments*
Other intangible assets, such as R&D and advertising, might also affect firm-level performance variation. Both R&D and advertising are highly concentrated in a small number of industries. We discuss R&D in more detail in section 6 and in Appendix II.

*Foreign Exposure*
A firm's reliance on foreign sales may affect its performance variation. However, whether foreign sales affect firm-specific or systematic (market- and industry-wide) volatility remains as an empirical question. For example, if firms in an industry mainly trade with a specific country, most of the volatility that comes from international business is mainly systematic (industry specific) volatility. On the contrary, if firms in the industry trade with many different countries whose economies exhibit low correlations with each other, it could affect firm-specific volatility in the industry. We calculate the ratio of foreign sales to total sales to capture the effect of foreign exposure on volatility using the segment data of COMPUSTAT.

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predicts stronger increases in firm-level volatility in manufacturing, as opposed to sectors that mainly produce non-tradable goods. However we find strong increases in firm-level volatility in both.

[24] Alternatively, IT might amplify price competition. Using data on individual life insurance policies, Goolsbee and Brown (2002) find that the growth of the Internet reduced term life premium by 8 to 15%. This is consistent with the Internet reducing search costs and thus stimulating price competition.

[25] In fact, firm size distribution becomes more dispersed due to creative destruction through IT investment. By including this variable in our regression may unduly underestimate the significance of IT variables. As will be discussed in section 6, even after including this variable does not change the effect of IT at all.

[26] Another possible story that predicts a negative relationship between investment and volatility is a 'declining industry' effect. If many firms are exiting a declining industry, high volatility might be associated with a low investment rate. In this sort of 'plain destruction', as opposed to 'creative destruction', systematic volatility should plausibly be elevated more than firm-specific volatility.

*Firm Diversification*[27]

A large literature links corporate diversification with both corporate governance problems and access to capital. In both cases, firm performance volatility could be affected.[28] Our firm diversification measure for each industry is the average number of two-digit segments reported in business segment data in COMPUSTAT.

*Other Control Variables*

Leverage is another candidate. A fall in the market value of a leveraged firm increases the volatility of its stock return and accounting earnings. Consequently, industries in which firms are more leveraged might exhibit greater cross-sectional performance variation.[29]

Liquidity might also affect performance variance. The easing of liquidity constraints should increase investment by previously constrained firms, but not other firms.

## 3. Construction and Characteristics of the IT Variable

This section outlines the construction of the IT variable. It then examines the variable's characteristics.[30] The appendix provides technical details.

We calculate industry-level IT data from *Fixed Reproducible Tangible Wealth* (henceforth FRTW) published by the *Bureau of Economic Analysis* (BEA). These data list investment in 61 different types of assets at the two-digit (1987 SIC code) industry-level.[31] We define the IT capital as the sum of seven types of computer hardware (mainframe computers, personal computers, direct access storage devices, computer printers, computer terminals, computer tape drives, and computer storage devices) and three types of software (pre-packaged software, custom software, and own-account software).[32]

We use the Törnqvist index to aggregate these ten types of computer hardware and software into IT capital.[33] Using the same data, we define non-IT capital as all other asset types. Thus, the total capital is the sum of IT and non-IT capital.

IT capital is distinguished from other capital by a rapid decline in its constant quality price index during the last few decades. The BEA uses the hedonic price method to estimate constant quality prices of computers.[34] The hedonic price falls as the quality

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[27] Unlike other control variables, the foreign exposure and firm diversification measures are calculated from COMPUSTAT segment data. Currently these data are available from 1985 on at WRDS. Reporting conventions for these data changed substantially in 1998. Thus the data range is different from that for other variables. Restricting our regressions accordingly does not qualitatively change our results as will be discussed in section 6.

[28] Refer Durnev *et al*. (2004) for further discussion.

[29] However, one should note that Black's hypothesis on the effect of leverage is mainly about the time-series causality between return and volatility and does not have much implication on the cross-sectional property. We investigate whether the cross-sectional variation of leverage has an effect on the cross-sectional variation of volatility measures.

[30] In appendix II, we compare IT and R&D, another possible source of creative destruction, in detail.

[31] See Herman (2000) and for a detailed description of the data set.

[32] A recent comprehensive revision of the *National Income and Product Accounts* published by the BEA categorizes expenditure on software as fixed investment rather than costs of materials, as in COMPUSTAT.

[33] For further details, see Appendix I.

[34] See BEA (1998) for the hedonic price method used by the BEA. In general, quality improvement is faster in computers than in software.

of computers rises.[35] For example, the memory chip capacity increased at 35 to 45% per year, a stylized fact known as Moore's law. Reflecting this rapid improvement in quality, the price of computers falls about 20% per year. This implies that real investment in computers can increase at 20% per year without changing nominal spending. This quality improvement is an important factor magnifying the rise in nominal IT investment. The real stock of IT capital also rose rapidly, but less so than real IT investment because of IT's high depreciation rate – about 30% per year. In this context, Jorgenson (2001) argues that swiftly falling prices in IT provide powerful economic incentives for firms to substitute IT for other inputs, like conventional capital and labor.

Three important episodes demarcate IT investment: the introduction of mainframes in the late 1970s, the introduction of personal computers from the early to mid-1980s, and Internet investment (a huge investment boom in hardware, software, and communication equipment) in the late 1990s. Throughout, software investment trended up as a share in total IT spending, exceeding hardware investment in the 1990s.

Table 1 shows the cross-industry distribution of IT intensity in 1970, 1980, 1990, and 2000. IT intensity is the ratio of the IT capital stock to the total capital stock.

On average, IT is more intensively used in the service sector than in manufacturing. However, there is a substantial variation of IT intensity within both sectors. Within manufacturing, IT intensity is high in *industrial equipment (including computer-producing firms)*, *electronic equipment (including semiconductor firms)*, *instruments (including laboratory and medical instruments)*, *apparels*, and *printing and publishing*. Within the non-manufacturing sector, *wholesale* and *business (including software firms)*, *legal*, and *other service industries* exhibit high IT intensity.[36] *Agriculture*, *mining*, *transportation*, and *utilities* all have low IT intensity. Figure 3 illustrates the distribution of IT intensity in 2000 across industries. Figure 3 shows that IT spending is almost normally distributed across all 50 industries. In contrast, Figure 4 shows R&D, another possible source of creative destruction, to be highly concentrated in certain industries. We discuss more about the different characteristics of IT and R&D in section 6 and in the appendix II.

## 4. Correlation Patterns of Sales Growth Rate, ROA, and Stock Return

### *4.1 Construction of the Data Series*

In this section, we investigate the volatility and correlation patterns of sales growth rate, ROA, and stock return to show increased heterogeneity among firms in the U.S. economy. We first estimate the volatilities of aggregate sales, aggregate ROA, and stock index return. We then calculate the averages of firm-level volatilities.

To calculate aggregate sales, we sum the real sales of all the firms in our sample

$$ASales_t = \sum_{i=1}^{N_t} Sales_{i,t} \quad (1)$$

[35] Declines in the hedonic price of computers (or equivalently, improvement in the quality of computers) depend on productivity growth associated with technological innovations in IT producing industries such as semiconductors and computer manufacturing industries. For example, Chun and Nadiri (2002) decompose the sources of productivity in the U.S. computer industries into process and product innovations. In a similar vein, Irwin and Klenow (1994) and Jovanovic and Rousseau (2002) argue that learning-by-doing is a major determinant of productivity growth in the semiconductor industry.

[36] Financial industry is also one of heaviest users of IT within the non-manufacturing sector.

where $N_t$ is the number of firms in quarter $t$ and $Sales_{i,t}$ is real sales of firm $i$, equal to nominal net sales (COMPUSTAT quarterly item 12) divided by the relevant price index of industry gross output.[37] Aggregate annual real sales growth is then

$$\frac{Asales_t - Asales_{t-4}}{\frac{1}{2}(Asales_t + Asales_{t-4})}. \tag{2}$$

Analogously, the quarterly real sales growth rate of firm $i$ in industry $j$ is defined as

$$\frac{Sales_{i,j,t} - Sales_{i,j,t-4}}{\frac{1}{2}(Sales_{i,j,t} + Sales_{i,j,t-4})} \tag{3}$$

where $Sales_{i,j,t}$ represent real sales of firm $i$ in industry $j$ at quarter $t$. In calculating firm-level sales growth rate, we exclude firm-quarter observations with footnotes in COMPUSTAT. Footnotes flag unusual events, such as mergers, accounting changes, discontinued operations, and the like. Such events render sales growth estimates problematic. However, our results are qualitatively similar if we retain these observations. After calculating aggregate and firm quarterly sales growth rates, we measure their volatilities (standard deviations) using five-year rolling windows.

Aggregate ROA and its volatility are defined similarly.[38] For each quarter $t$, aggregate total assets and aggregate operating income after depreciation are defined as

$$ATA_t = \sum_{i=1}^{N_t} TA_{i,t}, \tag{4}$$

$$AINCOME_t = \sum_{i=1}^{N_t} INCOME_{i,t} \tag{5}$$

for $N_t$ the number of firms, and $TA_{i,t}$ and $INCOME_{i,t}$ the total assets (quarterly item 44) and operating income (quarterly item 21 minus quarterly item 5) , respectively, of firm $i$ in quarter $t$. Aggregate ROA for quarter $t$ is thus

$$AROA_t = \frac{AINCOME_t}{\frac{1}{2}(ATA_t + ATA_{t-1})}. \tag{6}$$

The quarterly ROA of firm $i$ in industry $j$ is defined as

$$\frac{INCOME_{i,j,t}}{\frac{1}{2}(TA_{i,j,t} + TA_{i,j,t-1})} \tag{7}$$

[37] See the appendix for the construction of the price index of industry gross output.
[38] Total assets are not available on a quarterly basis until 1976. Thus, we calculate micro and macro volatilities of ROA from 1981.

where $INCOME_{i,j,t}$ and $TA_{i,j,t}$ represent the operating income[39] and total assets of firm *i* in industry *j* at quarter *t*. As with sales growth, we drop firm-quarter observations with footnotes. Again, our results do not change qualitatively if we retain these observations.

To calculate stock return volatilities, we use monthly stock return data from CRSP for 1971 through 2000. Again we use a five-year rolling window to calculate volatility for a given year. Aggregate volatility is the volatility of the value weighted portfolio consisting of all firms in both COMPUSTAT and CRSP. To gauge micro volatility, we average firm-level volatilities.

### *4.2 Volatility and Correlation Patterns*

As discussed in Section 1, Figure 1 shows both the aggregate (dotted lines) and firm-level (solid lines) volatilities of real sales growth, ROA and stock returns. Firm-level volatilities are equally-weighted averages of individual firm volatilities. Value weighting generates similar patterns. Firm-level volatilities are clearly higher than aggregate volatilities, and the gap between them rose steadily over the decades. For example, the difference between firm and aggregate sales growth volatilities was 0.184 in 1971, but grew to 0.346 by 2000. The increased differences are much larger for ROA volatilities, rising from 0.015 in 1981 to 0.17 in 2000[40] and stock return volatilities, rising from 0.043 in 1971 to 0.133 in 2000. When we partition firms into size quintiles, Figure 5 reveals similar patterns in each, with the largest change in the smallest firms. Rising firm-level volatility relative to aggregate volatility is evident across the entire corporate sector. This divergence implies declining correlations across firms over the same period.

Figure 6 reports average correlations across pairs of firms for sales growth, ROA and stock returns – first for the full sample of firms and then for the largest quintile, smallest quintile, and then between largest and smallest quintiles separately. Correlations of stock returns are, on average, higher than correlations of sales growth and ROA. However, all three exhibit similar declines. Correlations within the largest quintile are usually higher than those in the other groups, but also exhibit strong downward trends. These figures clearly show that something changed in the U.S. economy to make individual firms more heterogeneous.

It is useful to formalize the firm-specific and systematic components of the volatility in firm-level outcomes to motivate our empirical tests in the following section. Suppose firm-level performance measure can be represented by a simple linear structure.

$$r_{i,t} = \eta_t + \varepsilon_{i,t} \tag{8}$$

where $r_{i,t}$ represents the sales growth, ROA, or stock return of firm *i* in period *t*, $\eta_t$ represents a component common to all firms, and $\varepsilon_{i,t}$ represents a component specific to firm $i$. The correlation between firms $i$ and $j$ is

[39] Operating income after depreciation is not readily available in the quarterly COMPUSTAT file, but is available in the annual data (annual item 178). However, it can be estimated as operating income before depreciation (quarterly item 21) minus the depreciation and amortization (quarterly item 5).

[40] If we use the median of firm volatilities for ROA, the difference between firm level and aggregate volatilities rises from 0.011 in 1981 to 0.021 in 2000, which is more comparable with the results of the other two firm performance measures.

$$\rho(r_{i,t}, r_{j,t}) = \frac{\text{cov}(r_{i,t}, r_{j,t})}{\sigma(r_{i,t})\sigma(r_{j,t})} = \frac{1}{1 + (\sigma^2_{\varepsilon,t} / \sigma^2_{\eta,t})} \tag{9}$$

where $\sigma^2_{\eta,t}$ is the common variance component and $\sigma^2_{\varepsilon,t}$ is the firm-specific component of variance, which we take to be homogeneous across firms. The magnitude of the correlation thus depends on the ratio $(\sigma^2_{\varepsilon,t} / \sigma^2_{\eta,t})$. A lower correlation across firms could reflect either greater firm-specific variation or lower common variation, or both.

## 5. Decomposition of Volatility Series

This section describes how we decompose volatilities into firm-specific and systematic components. Our purpose is to isolate the idiosyncratic component that is not associated with general market- and industry-wide movements. In this regard, we follow Roll (1988) in distinguishing the 'firm-specific' variation from the sum of market- and industry-related variations. For simplicity, we refer to the latter sum as the 'systematic' variation.

To achieve necessary decomposition, we run the following regression specification used in Durnev *et al.* (2004):

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} r_{m,t} + \beta_{i,j} r_{j,t} + \varepsilon_{i,j,t} \tag{10}$$

where $r_{i,j,t}$ are real sales growth rate, ROA, or stock return for firm $i$ in industry $j$ at time $t$ ($t$ represents quarter for real sales growth rate and ROA and month for stock return). $r_{m,t}$ and $r_{j,t}$ are the market index and industry indices, and are value weighted averages excluding the firm in question. This exclusion prevents spurious correlation between firm and industry returns in industries that contain few firms. We run the regression for five-year rolling periods. Thus, we have the maximum of 20 observations for real sales growth rate and ROA and 60 observations for monthly stock returns.[41]

Firm-level regression results are aggregated to obtain the industry-level volatility measures. We calculate the absolute firm-specific variation and absolute systematic variation within industry $j$ as follows:

$$\sigma^2_{\varepsilon,j} = \frac{\sum_{i\in j} SSR_{i,j}}{\sum_{i\in j} T_i} \tag{11}$$

$$\sigma^2_{m,j} = \frac{\sum_{i\in j} SSM_{i,j}}{\sum_{i\in j} T_i} \tag{12}$$

where $SSR_{i,j}$ and $SSM_{i,j}$ are the unexplained (squared sum of residual errors) and

[41] We repeat our exercise for various restrictions on number of observations in each regression. However the results of the paper are not very different from one another. Here, we report results based on restrictions on observations where 15(30) or more observations are available for sales growth rate and ROA (stock return). If we impose no restrictions, which basically means we include all young firms, there is slight improvement in the statistical significance of the results.

explained variations of firm $i$ in industry $j$. The sums in (11) and (12) are scaled by number of firm-quarter (or firm-month) observations available in industry $j$. Thus, the industry-wide average $R_j^2$ can be defined as follows:

$$R_j^2 = \frac{\sigma_{m,j}^2}{\sigma_{\varepsilon,j}^2 + \sigma_{m,j}^2}. \tag{13}$$

Panels A, B, and C of Figure 7 show the time-series patterns of the equal and value-weighted averages of each variation measure. To obtain value-weighted measures, we calculate equally weighted averages across all firms in an industry and then apply the industry weight. For real sales growth rate and stock returns, data start in 1971 (based on the years between 1967 and 1971) while ROA starts from 1981 (because the quarterly ROA data begin in 1976).

Several patterns emerge from these figures.

First, idiosyncratic variation increased dramatically in sales growth, stock returns, and, to a lesser degree, ROA. Equal and industry value weighted figures look very similar. Increasing idiosyncratic volatility is not confined to a few large industries.

Second, Table 2 shows idiosyncratic volatility to be much larger than systematic volatility. For each year and each industry, we first calculate the ratio of idiosyncratic volatility to systematic volatility, and then calculate the means and medians of these ratios for the whole sample and two sub-periods – 1971-1983 and 1984-2000. The choice of 1984 as the break point is reflects the general agreement among economists that the U.S. economy exhibits a structural break at that time.[42] The ratio medians reported in the table indicate that the idiosyncratic volatility in the whole sample is three times as large as the systematic volatility in real sales growth and ROA, and about five times larger for stock return. The divergence between idiosyncratic and systematic volatilities becomes more pronounced in the second sub-period in general, especially for stock returns and ROA. Reflecting this rising idiosyncratic volatility, the industry average $R^2$ also declines over the sample period (Figure 7). For real sales growth and stock returns, $R^2$ declines by about 50% from the mid-1970s to the end of the sample period.

Third, since the mid-1970s, the $R^2$ of stock returns provides a lower bound for the $R^2$ of the other two measures. This faster rise in idiosyncratic relative to systematic volatility for stock returns might reflect additional factors at work in that measure alone – such as reduced arbitrage costs and Internet investing. However, rising idiosyncratic volatility is clearly not just confined to stock returns. It is observed in real sales growth and ROA as well over the whole sample period.

Fourth, in general, absolute idiosyncratic and absolute systematic variations are strongly positively correlated with each other for all three variables (Panel B of Table 2). A positive correlation is most apparent for ROA. In firm-level regressions, a positive correlation implies dependence between the independent variable and residual that produces inconsistent estimators. However, in this case, the correlation is between two aggregate measures calculated to represent industry-level average firm-specific and

[42] See Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and others for more detailed discussions.

systematic volatilities. This makes it possible to have a positive correlation between the two measures even if there is no correlation problem in the firm-level regression. In fact, this positive correlation is useful in inferring the sources of firm-specific variation, for it suggests that much firm-specific variation is heterogeneous reactions to market-wide shocks. That is, firms often react differently when hit by the same economy-wide shock, thus inducing firm-specific variation.

Fifth, ROA volatility follows a pattern somewhat different from that of the other two series. The correlation between absolute idiosyncratic and absolute systematic volatility is largest for ROA, and consequently the decrease in its $R^2$ is smallest. Part of the high correlations might be due to outliers: there are several sharp spikes in the comovement of absolute idiosyncratic and absolute systematic volatility. Dropping both extreme 1% tails of firm-year observations causes the absolute idiosyncratic and absolute systematic ROA volatilities to resemble those of stock returns and sales growth rates. Extreme values in ROA are much more frequent than in stock returns and sales growth rates.[43] Another possibility is that earnings might be ‘managed’, while sales and stock return are not. For example, if firms manage their earnings more when the economy exhibits more volatility, we would see a larger positive correlation between absolute idiosyncratic and absolute systematic measures for ROA. To address this issue, we use cash flow to asset ratios after controlling for accruals using the method of Chan *et al.* (2001). This generates qualitatively similar results. Further investigation is needed to clarify these issues.

## 6. Regression Analyses

In this section, we test whether industries with higher IT intensity exhibit larger idiosyncratic variation. First, we examine the bivariate relationships between our volatility measures and IT intensity (the ratio of IT capital to total capital). We use this rather than current IT investment because our focus is the extent to which the *utilization of information technology* affects cross-sectional patterns of volatility. Creative destruction plausibly depends not just on current IT investment, but on IT intensity – firms’ overall abilities to apply IT to their ongoing businesses. Second, we investigate the effect of IT intensity on volatility measures in a multiple regression framework controlling for the other industry characteristics described in Section 2.2.

### *6.1 Bivariate Regressions*

We run weighted least square regressions (WLS) for each year and report Fama-MacBeth coefficients and *t*-statistics.[44] In calculating Fama-MacBeth *t*-statistics, we adjust for possible serial correlation and heteroskedasticity in coefficient estimates using the method of Newey and West (1987) as modified in Pontiff (1996).[45] All variables are transformed by taking natural logarithms. We exclude financial industries (1987 SIC

[43] One cause of these outliers is very small total asset figures.

[44] All regressions are weighted by the industry share of market capitalization, sales, and total assets for stock return, sales, and ROA, respectively. However, the results are not sensitive to using different weights.

[45] As Jin and Myers (2004) note, this may be an overcorrection since spurious serial correlation is pssible in small sample coefficient estimates even if the estimation errors for the coefficients are uncorrelated. However, we follow Pontiff (1996) and Jin and Myers (2004) in taking a conservative approach in calculating t-statistics.

codes from 6000 to 6999) because of accounting data (such as sales and ROA) incompatible with that in other industries. Thus, the maximum number of industries is 50, consisting of 20 manufacturing and 30 non-manufacturing industries.[46] We also discard industries containing fewer than 5 firms, and industries whose IT stock is not defined. The tables also report the average number of industries used in the regressions.

Table 3 presents regressions using IT intensity to explain three types of volatility (absolute idiosyncratic, absolute systematic and idiosyncratic relative to systematic) for each volatility measure (sales growth, ROA, and stock returns). Since the $R^2$ measure is confined within the unit interval and highly skewed, we apply a logistic transformation as in Durnev *et al*. (2004):

$$\psi_j = \ln\left(\frac{1-R_j^2}{R_j^2}\right) = \ln(\sigma_{\varepsilon,j}^2) - \ln(\sigma_{m,j}^2)\,. \tag{14}$$

We report regression results for the whole sample (from 1971 to 2000 for stock return and sales growth rate and from 1984 to 2000 for ROA) and for two sub-periods.[47]

The central finding is that absolute idiosyncratic variation is strongly positively correlated with IT intensity. Figure 8 (Panels A, B, and C) graphs the relationship between IT intensity and idiosyncratic volatility in 2000. IT intensity is also positively correlated with absolute systematic variation. However, discussed below, the positive correlation between absolute systematic measure and IT intensity appears due to a strong positive correlation between IT intensity and other control variables (especially, R&D) that explain much of systematic volatility.

The logistically-transformed $R^2$ measure in (14), denoted $\psi$, captures the relative importance of absolute idiosyncratic versus absolute systematic volatility. IT intensity is positively related to $\psi$ for the full sample period for stock returns. This relationship is significant at 1%, and its analogue for sales growth is significant at 10%. Sales growth is more strongly correlated with $\psi$ in the second subperiod, with a significance exceeding 1%.

However, the results for ROA are weak. Even though IT intensity explains absolute idiosyncratic volatility, it fails to explain $\psi$ – and even has wrong sign (negative). However, as discussed below, the significant negative coefficient disappears if we include other control variables in multiple regressions. This suggests that the negative coefficient on IT is picking up other industry characteristics.

The bivariate regressions involving returns volatility in Table 3 have substantial adjusted $R^2$s – over 40% for the whole sample for the absolute idiosyncratic regressions. The $R^2$s are nearly as high form the sales growth and ROA volatility regressions.

We can think of two reasons for a weaker relationship with sales growth and ROA than with stock returns. First, the volatilities of sales growth and ROA must be estimated

[46] The number of industries used in this paper is almost the same as in Hobijn and Jovanovic (2001) and Stiroh (2002).

[47] The results for ROA are reported for the second subperiod only. Quarterly ROA data are available from 1976 on, so we could theoretically obtain decomposed volatility series from 1980 on. However, we require more than five firms in an industry to calculate ROA volatility series, and this condition is met in only thirty industries through the early 1980s. Thus we perform regression from the mid 1980s for ROA.

using quarterly observations. Stock returns, however, can be estimated using monthly data, and so are more precise. Second, we might have an omitted variable bias. If missing control variables capture systematic volatility and are correlated with IT intensity, our estimated coefficients of IT intensity are biased. To address this issue, we move on the multiple regressions analyses.

*6.2 Multiple Regressions*

In this section, we include all the industry-level control variables described in Section 2.2 in our regressions. These controls are: average firm age, non-IT capital investment rate (I/K), Herfindahl-Hirschman Index, leverage, liquidity, firm size distribution, foreign exposure, firm diversification, and measures of intangibles such as R&D, advertising, and book-to-market ratio.[48]

Table 4 reports the averages of annual cross-sectional correlation coefficients and their associated significance levels. Note that IT intensity is strongly positively correlated with R&D and advertising spending. This suggests possible complementarities between intangibles. IT intensity also positively correlates with non-IT capital investment and liquidity, implying that more rapidly growing and less cash constrained industries invest more in IT. The book-to-market ratio, which in many studies use to proxy for intangible assets, is negatively correlated with IT. Intriguingly, IT is the only variable correlated with all the other intangible measures. For example, R&D is correlated with IT and book-to-market, but not with advertising spending. Firm diversification is negatively correlated with both IT and non-IT capital investment, though the latter is insignificant. This could reflect more diversified firms delaying investment.

We isolate the independent contribution of IT to volatility by including all of these variables in the regressions in Table 5. Because business segment data are unavailable for earlier years, the foreign exposure and firm diversification measures are not included. Table 6 reports analogous regressions including these two additional controls.

The key results from Tables 4, 5 and 6 are as follows.

First, IT is significantly positively correlated with idiosyncratic variation – both absolute and relative to systematic variation. In fact, IT is the only variable that explains both with consistent positive signs and significance levels. These findings survive the inclusion of all of the control variables discussed above. This is consistent with the use of information technology being related to creative destruction, which increases heterogeneity among firms.

Second, IT intensity is not significantly related to systematic volatility. Including controls, especially R&D intensity, renders IT insignificant in regressions explaining systematic volatility.[49] The component of IT related to systematic variation is thus correlated with R&D intensity, and this explains the significant relationship between IT and systematic volatility in bivariate regressions. Also, IT attracts a positive and significant coefficient in regressions explaining idiosyncratic relative to systematic

[48] See Appendix I for the construction of each variable.

[49] As noted above, R&D is quite concentrated in the manufacturing sector, which is perhaps subject to more business cycle risk than other sectors. To control for this, we include a manufacturing sector dummy along with IT intensity and R&D. R&D remains significant, suggesting its coefficient is not a mere artefact of business cycle exposure.

volatilities in both sales growth and stock return; but R&D does not. Overall, IT seems related to idiosyncratic volatility, while R&D appears related to systematic volatility. Appendix II explores this further by discussing different characteristics of IT and R&D that might explain this.

Third, the signs and significance of IT intensity are very stable. This is in stark contrast to the coefficients of the various controls, which are quite sensitive to the particular specification in many cases. We return to this below.

Fourth, by adding control variables, negative relationship between IT intensity and logistically-transformed $R^2$ measures in bivariate regression disappears. However, still we could not get positive and significant relationship between the two measures either.

Since many of the control variables have multiple interpretations, we refrain from interpreting their coefficients and significance levels. Also, many of the control variables are quite sensitive to the particular regression specification. For example, when only IT intensity, age, I/K (non-IT investment over non-IT capital stock) and book-to-market ratios are included, book-to-market is negatively related to absolute idiosyncratic or systematic volatility. However, when we include more variables, the sign becomes positive for the absolute volatility measures. This instability makes interpreting the variable problematic. However, there are a few variables that tell consistent stories. The Herfindahl-Hirschman Index (HHI) attracts positive and significant coefficients in regressions explaining relative idiosyncratic volatility in both stock returns and sales growth rates. However, HHI is negatively related with both absolute volatility measures. Combining these results implies that a higher HHI depresses systematic volatility more than idiosyncratic volatility. Advertising is also negatively related with both absolute volatility measures, but positively related to idiosyncratic relative to systematic volatility. These findings are consistent with monopoly power and brand names helping firms smooth their performance *and* rendering creative destruction less necessary. Firm age is typically negatively related to both absolute volatility measures, but its explanatory power for idiosyncratic relative to systematic volatility is slight. Older industries are perhaps more stable, and might also be less affected by creative destruction. Industries in which all firms are nearly the same size exhibit lower volatility – both idiosyncratic and systematic. Note also that including firm diversification and foreign exposure in the Table 6 regressions barely changes the explanatory power of IT intensity for all the volatility measures.

*6.3 Robustness Checks*

We repeat our empirical exercise in several different ways. First, we check whether the *de minimus* restriction on the number of observations used in calculating our volatility measures affects the results. Second, we check whether outliers drive the results by cutting off the extreme 1% from both tails of the total distribution of each volatility measure. Third, we check whether the inclusion or exclusion of footnote stamped data from COMPUSTAT alters the results. Fourth, we try nominal rather than real IT intensity in our regressions. None of these alternative approaches qualitatively changes our results.

*6.4 Endogeneity*

We have shown that industries with greater IT intensity exhibit greater idiosyncratic volatility. However, we have not resolved whether IT intensity causes idiosyncratic variation. The converse might be true, or a third factor might cause both.

The converse, that high idiosyncratic volatility causes IT intensity might follow if more volatile industries invest more in IT capital to decrease the volatility through, for example, better inventory management. This implies declining firm level volatility over time as IT intensity rises, which is testable.

A third factor merits consideration if buttressed by a plausible economic explanation. One possibility is that high idiosyncratic volatility reflects pre-existing heterogeneity among firms that is unrelated to creative destruction, and that this heterogeneity correlates with the marginal productivity of IT. Again, this is testable.

To test whether IT intensity reflects pre-existing heterogeneity, lowers volatility, or raises it, we regress

$$\Delta Vol_{j,t+1} = \alpha + \beta(IT)_{j,t} + \gamma Vol_{j,t} + \varepsilon_j \tag{15}$$

where $\Delta Vol_{j,t+1}$ is a five-year log difference of one of our volatility measure[50] (absolute idiosyncratic, absolute systematic, or idiosyncratic relative to systematic) for industry $j$, $IT_{j,t}$ is IT intensity for industry *j*, and $Vol_{j,t}$ is volatility of industry *j* at time *t*. We include $Vol_{j,t}$ to control initial differences in the level of volatility. If IT intensity raises idiosyncratic volatility, $\beta$ should be positive in the absolute and relative idiosyncratic volatility specifications of (15). If high volatility induces IT investment aimed at reducing volatility, we expect a negative $\beta$. If IT investment is correlated with pre-existing high volatility, $\beta$ should be insignificant.

The regression specification in equation (15) resembles those used in the economic growth literature, for example in Barro and Sala-i-Martin (1995). In this literature, special attention attaches to $Vol_{j,t}$ because, in cross-sectional regressions, the residuals, $\varepsilon_j$, may contain a common factor that affect all the industries. If this factor is correlated with $Vol_{j,t}$, its regression coefficient is biased. In our case, this problem does not arise in specifications using absolute idiosyncratic volatility because, by construction, that measure is independent of common shocks. There can thus be no relationship between the residuals and $Vol_{j,t}$. However, specifications using absolute systematic volatility or idiosyncratic relative to systematic volatility could be vulnerable to this problem. Consequently, caution is warranted in interpreting results for these two volatility measures.

Table 7 reports Fama-MacBeth regression coefficients for (15), along with t-statistics robust to serial correlation and heteroskedasticity. The results can be summarized as follows:

Absolute idiosyncratic volatility rises after high IT intensity. The sole exception is absolute idiosyncratic stock return variation using the whole sample, where the coefficient is still positive, but the *t*-statistic is only 1.67. The coefficient is significant in

[50] Varying the time horizon by measuring the growth rate in volatility over the subsequent one, two, three, … ten years generates results qualitatively similar to those in Table 7

each sub-sample. Idiosyncratic relative to systematic variation also rises subsequent to high IT intensity. These results are most significant for the second subperiod, and relative idiosyncratic volatility in ROA is insignificant, mirroring our earlier cross sectional results. Note also that $\gamma$ is negative. Thus the intensity of creative destruction (measured by idiosyncratic volatility) tends to decrease, all else equal, in the absence of sustained IT investment.

Table 7 is consistent with IT intensity causing higher volatility, and difficult to reconcile with IT intensity being either aimed at reducing volatility or an artefact of pre-existing heterogeneity.

## 7. Conclusion

We find that higher firm-specific volatility in firm stock returns, sales growth, and ROA is associated with higher investment in IT. These findings are robust to a wide range of specification changes and to including as control variables: average firm age, concentration, other capital investment, leverage, foreign exposure, and spending on intangible asset like R&D. We also show that subsequent volatility growth is higher in industries with greater IT intensity.

Thus, investment in IT is associated with greater heterogeneity in firm performance within an industry. We propose that this reflects a divergence between winners and losers in devising profitable IT applications, and that the growing IT investment of the past decades hastened creative destruction, as described in Schumpeter (1912), as successful adopters flourished and other firms stagnated. Closely related to this, heterogeneity among successful adopters might also increase if IT investment permitted greater product differentiation, especially along intangible dimensions of output. Again, this lets winners diverge more sharply from losers.

This explains how volatility in economy aggregate stock market return, sales growth, and ROA fell while firm-level variation in stock returns, sales growth, and ROA all rose. The firm-specific components of the latter rose faster than their systematic components, thus decreasing their correlation across firms. This *fallacy of composition in volatilities* effect is greater in industries that invested more heavily in IT.

Our findings also explain why greater firm-specific volatility should be related to better developed financial systems and better economy performance. Better developed financial systems let a broader range of firms raise money and undertake IT investments at lower cost. More IT investment reflects, to some extent at least, more intensive creative destruction, and hence faster growth and higher standards of living.

Morck *et al.* (2000), Bris *et al.* (2004), Bushman *et al.* (2002), Durnev *et al.* (2004), and Jin and Myers (2004) present evidence consistent with interpreting firm-specific variation as a measure of stock market transparency. Our findings in no way undermine this view. Rather, more transparent stock markets might well permit more intensive investment in new technologies such as IT by making the capital needed to finance it cheaper. Nonetheless, stock market volatility clearly tracks the volatilities of fundamentals, limiting, but not necessarily eliminating, the viability of explanations of individual stock price comovement based on purely stock market-based explanations like investor herding.

R&D intensity behaves quite differently from IT intensity. Systematic (market-wide plus industry-related) variation measures based on stock returns and fundamentals are unrelated to IT intensity after controlling the effect of R&D intensity. The component of IT intensity related to systematic variation appears to be highly correlated with R&D intensity. R&D itself is primarily correlated with market-wide and industry-related comovement. This perhaps reflects underlying economic differences between R&D and IT related innovation. Further work is needed to clarify this.

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## Appendix I: Data Construction

*Price Index for Sales*

To calculate real sales, we divide nominal sales by the price index of two-digit level industry gross output obtained from *Gross Product Originating* (GPO), published by the Bureau of Economic Analysis (BEA).[51] GPO price index data are available only from 1977 on. To estimate pre-1977 price indexes, we use prices of gross output from Office of Employment Projection data produced by the Bureau of Labor Statistics (BLS).

*Construction and Aggregation of Capital Stock (IT and Non-IT)*

We construct the capital stock of asset $i$ in industry $j$ at time $t$ using the perpetual inventory method with asset-specific geometric depreciation rates ($\delta_i$). Thus a particular capital stock can be defined as

$$K_{i,j,t} = (1-\delta_i)K_{i,j,t-1} + I_{i,j,t} \tag{A.1}$$

where the depreciation rate of computers and software is about 0.31 (See Fraumeni (1997) for asset-specific depreciation rates.).

To aggregate $N$ types of capitals, we use the Törnqvist index, which is the geometric average of the price ratios of $N$ types of capitals between $t-1$ and $t$, or

$$\frac{P_t}{P_{t-1}} = \prod_{i=1}^{N}\left(\frac{p_{i,t}}{p_{i,t-1}}\right)^{S_i} \tag{A.2}$$

where $P_t$ is the aggregated price index of $N$ types of capitals at time $t$, $p_{i,t}$ is the price of capital of type $i$ at time $t$, and $S_i$ is the weight of capital of type $i$. $S_i$ is

$$S_i = \left(\frac{1}{2}\right)\left(\frac{p_{i,t-1}K_{i,t-1}}{\sum_i p_{i,t-1}K_{i,t-1}}\right) + \left(\frac{1}{2}\right)\left(\frac{p_{i,t}K_{i,t}}{\sum_i p_{i,t}K_{i,t}}\right). \tag{A.3}$$

Finally, the ratio of aggregate real capital stock is

[51] See Lum *et al.* (2000) for a detailed description of the GPO data set.

$$\frac{K_t}{K_{t-1}} = \left(\frac{\sum_i p_{i,t} K_{i,t}}{\sum_i p_{i,t-1} K_{i,t-1}}\right)\left(\frac{P_{t-1}}{P_t}\right). \tag{A.4}$$

*R&D and Advertising*
We obtain R&D expenditure (annual item 46) from COMPUSTAT, and deflate this using the price index of gross domestic product (GDP). Following the method of Chan *et al.* (2001), we construct real R&D capital stock as:

$$RDS_t = \sum_{k=0}^{4} (1 - k\delta) RD_{t-k} \tag{A.4}$$

where *RDS* is R&D capital stock, *RD* is R&D expenditures, and $\delta$ is a 20% straight-line depreciation rate.[52] We define R&D intensity as the ratio of real R&D capital stock to real PPE (annual item 8). PPE is deflated by the price index at the two-digit industry-level from the BEA FRTW. Using advertising expense (annual item 45), we also define advertising intensity as the ratio of advertising expense to PPE.

*Firm Age*
We construct age variable using two different method. First, we track the listing year from CRSP monthly data and measure calendar age of each firm. Second, following Hall (1990), we construct the average age of capital and use it as a proxy for the age of firm. We first calculate the age of capital of each firm as the ratio of accumulated depreciation to current depreciation and amortization (annual item 14) for the current year. Accumulated depreciation is defined as gross PPE (annual item 7) minus net PPE (annual item 8). Then we calculate the equally weighted average of individual firm ages within each industry to obtain industry-level estimates.

*Herfindahl-Hirschman Index*
We construct sales-based the Herfindahl-Hirschman index (HHI). HHI is defined as the sum of squared firm's share of sales within an industry

*Conventional Investment*
We also construct the capital investment rate (I/K) as the ratio of non-IT investment at time *t* to non-IT capital stock at *t-1* (in real terms) using the FRTW data set. We use a non-IT investment rate because the total investment rate might be correlated with IT intensity.

*Book-to-Market Ratio*
We calculate industry-level book-to-market ratio as the ratio of industry aggregate value of common equity (annual item 60) to market capitalization of common stock (annual item 25 multiplied by annual item 199).

[52] Most studies use 10-25% depreciation rate for R&D capital. For example, using the patent data, Pakes and Schankerman (1984) estimated the depreciation rate of R&D capital that varies from 18-36%, on average, 25%.

*Foreign Exposure*
To measure the extent of foreign exposure, we use COMPUSTAT geographic segment data. For each industry, we calculate the ratio of foreign sales to total sales. Currently, geographic segment information is available in COMPUSTAT from 1985 on from WRDS. However, a significant change in the Financial Accounting Standard Board's (FASB) segment reporting standards occurred in 1998, when SFAS No. 131 superseded the previous segment-reporting rules under SFAS No. 14. The new standard is effective beginning with December 1998 fiscal year-ends. Given this change, we calculate foreign exposure up to and including 1997.

*Leverage and Liquidity*
We estimate leverage as the ratio of the sum of short-term debt (annual item 34) and long-term debt (annual item 9) to total assets (annual item 6); while liquidity is defined as the ratio of current assets (annual item 4) to current liabilities (annual item 5).

*Distribution of Firm Size and Firm Diversification*
Refer section 2 for the construction of these two variables.

## Appendix II: IT vs. R&D

We hypothesize that IT affects volatility patterns in the U.S. economy *via* creative destruction. IT may not be the only investment that leads to creative destruction. Another highly plausible candidate is R&D. For example, Kothari *et al.* (2002) find that R&D investment has a stronger effect on future earnings variability than investment in property, plant, and equipment (PPE). Chan *et al.* (2001) find similar results using stock returns. Barron *et al*. (2002) find that the dispersion of analysts' forecasts is negatively associated with intangible assets, such as R&D and advertising. This appendix compares IT with R&D. In Section 6, we compare the relative importance of IT and R&D in explaining firm-specific (and systematic) volatility.

First, in contrast to IT investment, the distribution of R&D spending is highly concentrated in a few industries (See Figures 3 and 4.). Figure 4 shows the cross-industry distribution of R&D intensity (the ratio of R&D capital to PPE using nominal dollars) in 2000. R&D intensity is exceptionally high in five durable goods manufacturing industries, *chemical products (including pharmaceuticals)*, *business services (including software)*, and *other services (including R&D and testing services)*. In 2000, R&D spending by the *industrial machinery*, *transportation equipment*, and *chemical products* industries accounted for almost 80% of total R&D spending in the manufacturing sector (NSF, 2003).[53]

In contrast, more than 75% of industries have R&D intensities below one percent. And in a sizeable fraction of industries, most firms report no R&D activity whatsoever.

[53] According to a *National Science Foundation* survey (1999), nineteen out of the twenty firms with R&D spending greater than one billion dollars reside in four manufacturing industries. For example, IBM and Hewlett-Packard reside in *industrial machinery*; General Electric, Lucent, and Intel in *electric and electronic equipment*; General Motors and Ford in *transportation equipment*, and Johnson & Johnson and Pfizer in *chemical products*. Currently, COMPUSTAT classifies IBM as a *business service* firm because its sales of software and computer related services are greater than its sales of computer hardware.

Kothari *et al.* (2002) report a median R&D intensity of zero for 40% of two-digit industries.

In addition to being highly localized in certain large firms in a few industries, R&D seems aimed at developing specific sorts of tangible products. An NSF (1999) survey reports more than 70% of R&D spending used to develop new products such as machinery or medicines. Investment in these sorts of innovation is highly dependent on possessing large research infrastructures – well-equipped laboratories and highly educated researchers.

Schumpeter (1942) argues that innovations of this sort are best undertaken by large, quasi-monopolistic firms, or in partnership with them. These firms have sufficient internal cash flow to finance such infrastructure and sufficient stability to attract and keep risk-averse technical experts. In contrast, IT seems more like the turn-of-the-century electricity, steel, and machinery that inspired Schumpeter's (1912) description of creative destruction consisting of rapidly growing upstarts displacing established giants.

Thus R&D and IT investments may, at the present time in the U.S. economy, typically represent two qualitatively different forms of innovation. IT is a general purpose technology, whose application creates value proportional to certain complementary inputs, such as managerial talent and allows qualitative product differentiation in a broad cross-section of industries. Indeed, Figure 3 shows that IT spending is almost normally distributed over 50 industries. In contrast, Figure 4 shows that R&D is highly specific to certain firms in certain industries. Big R&D spenders are large, established firms with capital intensive on-going innovation programs of the sort described in Schumpeter (1942).

A second difference between IT and R&D is that the latter often provides a return only in the very long run – see, for example, Chan *et al.* (2001). New drugs, new automobile designs, and the like often require a decade or more of investment before generating positive cash flows. In contrast, IT investments seem to produce returns over much shorter horizons.

The prolonged uncertainty regarding the outcome of R&D investment might increase the systematic volatility of R&D intensive stocks and decrease their firm-specific volatility during certain periods. If all the major pharmaceuticals firms are racing to develop a new drug, their stocks tend to move together, reflecting changes in expected demand for the drug, as long as they look equally likely to win. This leads to industry-wide comovement. Once it becomes clear which firms are winning, their prices begin to diverge from those of the losers. This results in firm-specific volatility.[54] If long periods of uncertainty are punctuated by sudden revelations of who is winning, we might observe a high degree of comovement most of the time in R&D intensive industries.

Berk *et al.* (2004), citing the same prolonged R&D investment period, propose another mechanism through which R&D activity might correlate with systematic volatility. They point out that, unlike major capital investments, which are undertaken in a given year and then become sunk costs, investment in a given R&D project must continue over many years. For example, an oil company firm developing a new oilfield extraction technology must continue funding such an initiative for many years to expect a return, and generally reviews this funding commitment each year. Even if the future technological risk associated with the project is highly firm-specific, and thus

[54] This line of reasoning follows from Shiller (1989).

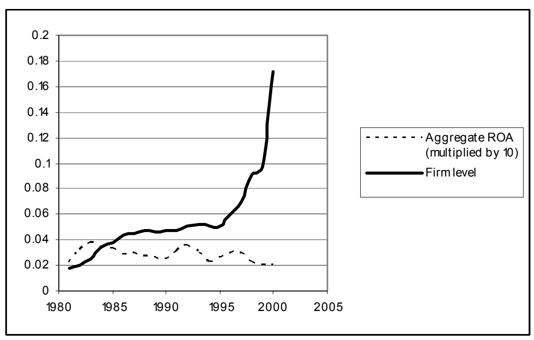
diversifiable, the decision each year about continuing the R&D project or not depends on systematic factors, such as the interest rate and the expected oil price after the completion of the project.

Some logic of this sort appears to apply to R&D, but not to IT. Section 6 shows that R&D intensity is related to systematic variation, and IT is entirely unrelated to systematic volatility after controlling for R&D intensity. Why this is so probably has to do with the differences listed above; however more work is clearly needed to clarify this.

**Figure 1. Aggregate (Macro) and Firm-Level (Micro) Volatilities, 1971-2000**
This figure plots aggregate and firm-level volatilities of real sales growth rate, return on asset (ROA), and stock return. Aggregate volatilities of real sales growth rate and ROA are calculated from the growth rate of aggregate real sales and aggregate ROA for all the firms in COMPUSTAT using 5 year rolling windows. Aggregate stock return volatility is calculated using the value-weighted portfolio consisting of all firms both in CRSP and COMPUSTAT using 5 year rolling windows. Firm-level volatilities are averages of volatilities of real sales growth rate, ROA, and stock return of all firms in the sample.

(a) Real sales growth rate


(b) ROA




(c) Stock return

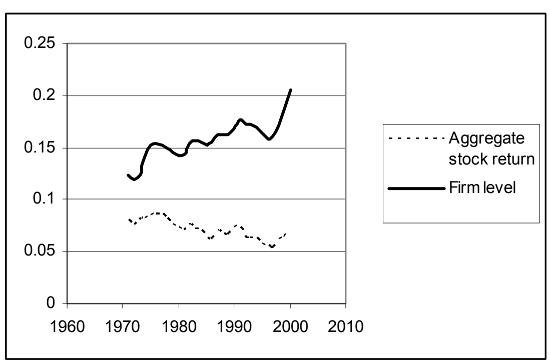
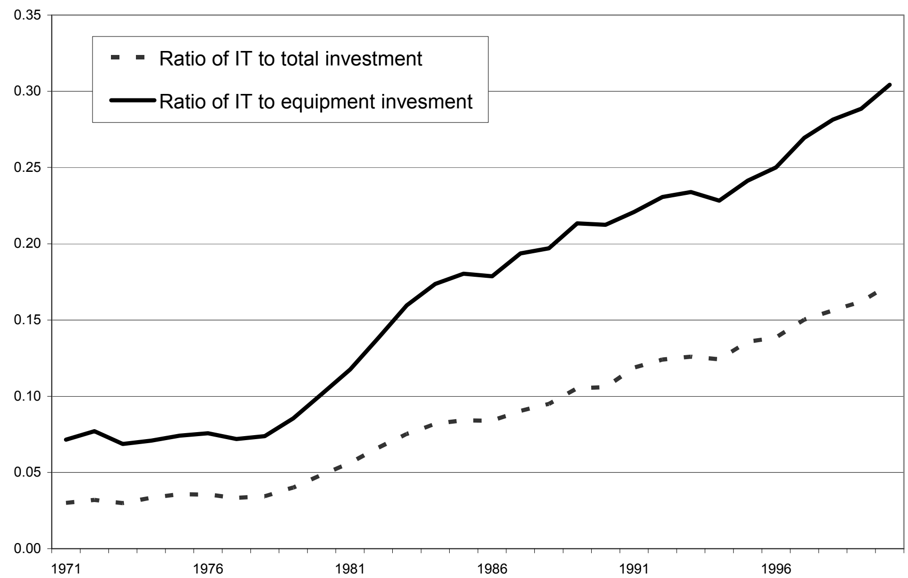


**Figure 2. Time-Series and Cross-Sectional Patterns of IT Investment, 1971-2000**
Figure 2(a) plots the share of IT investment in equipment and total investment in the U.S. (all in nominal dollars). IT investment is defined as the sum of computers and software investment. Total investment is the sum of equipment & software and structures. Figure 2(b) illustrates the cross-industry distribution of logarithm of IT intensity where IT intensity is measured as the ratio of IT capital to total capital in 1994 real dollars.

(a) Time-series pattern of IT investment




(b) Cross-industry distribution of logarithm of IT intensity

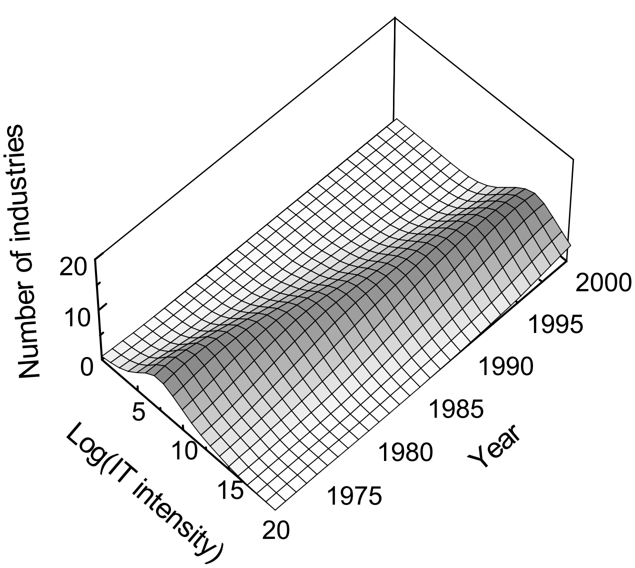


**Figure 3. Distribution of IT Intensity in U.S. Industries, 2000**
IT intensity is defined as the ratio of IT capital to total capital, all in nominal dollars.

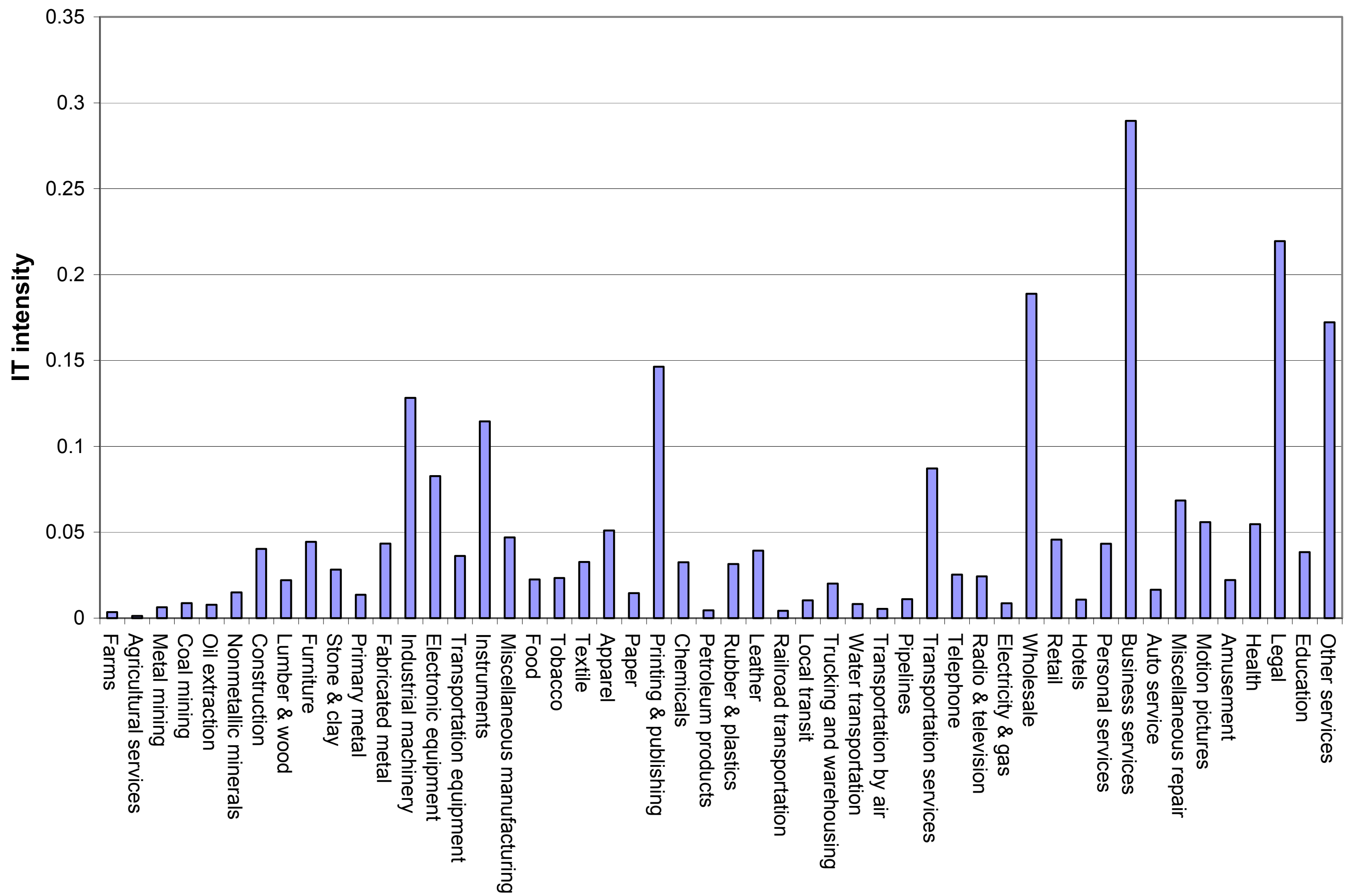


**Figure 4. Distribution of R&D Intensity in U.S. Industries, 2000**
R&D intensity is defined as the ratio of R&D capital to PPE, all in nominal dollars.

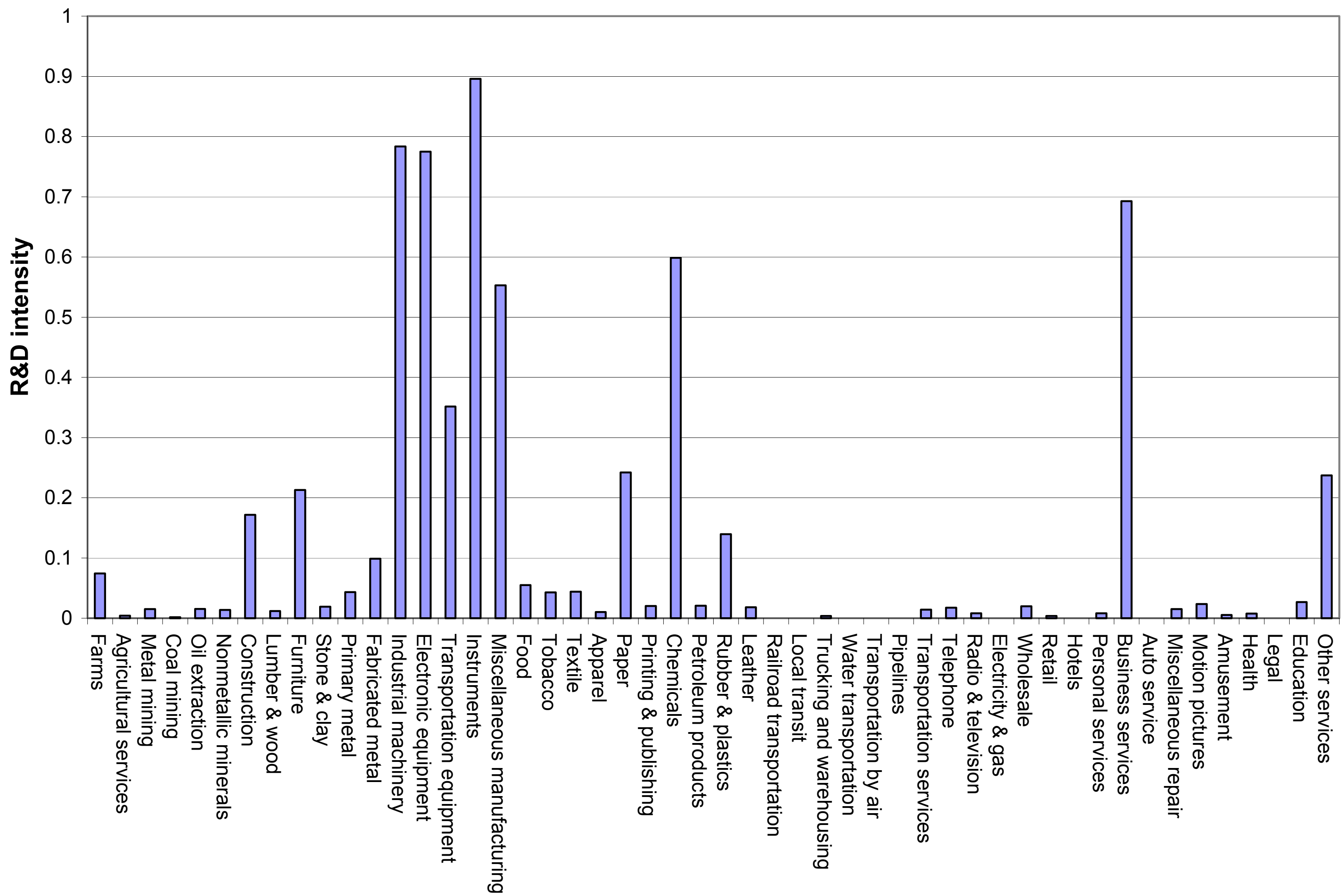
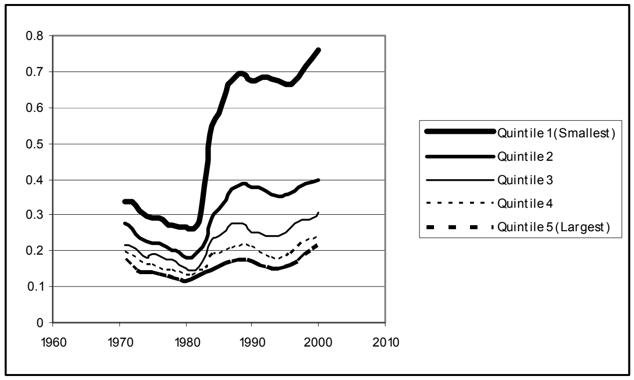
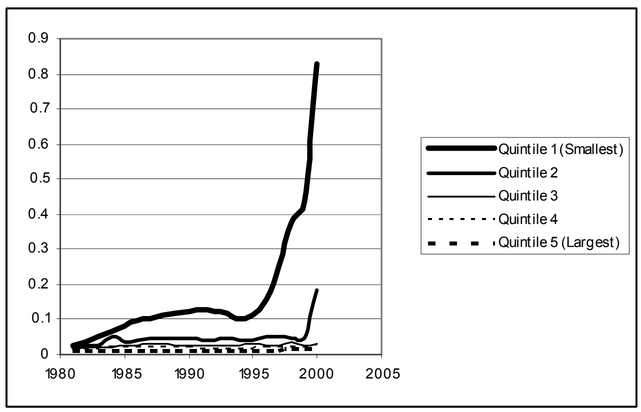


**Figure 5. Firm-Level Volatility by Size Quintiles**
This figure plots equally weighted average of firm-level volatility for each size quintile.

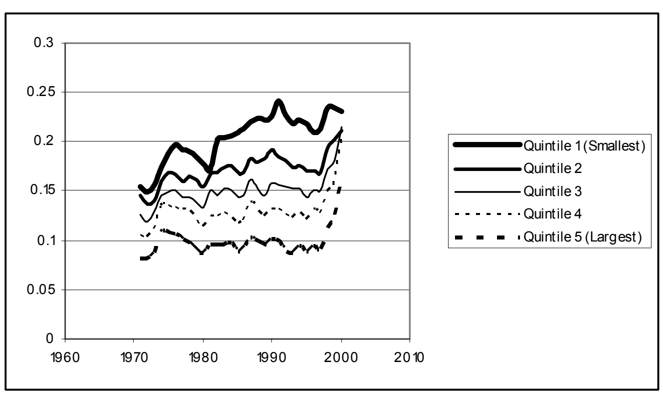
(a) Real sales growth rate




(b) ROA



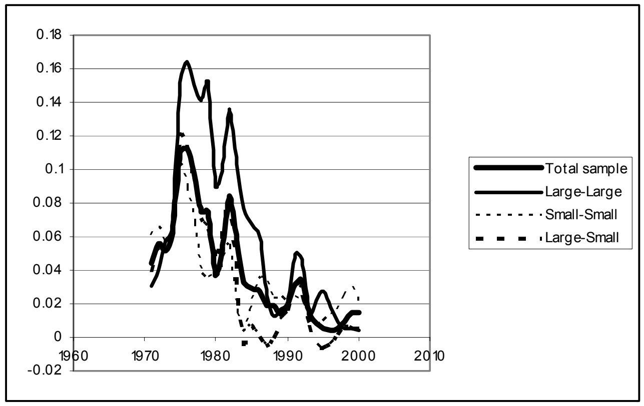

(c) Stock return



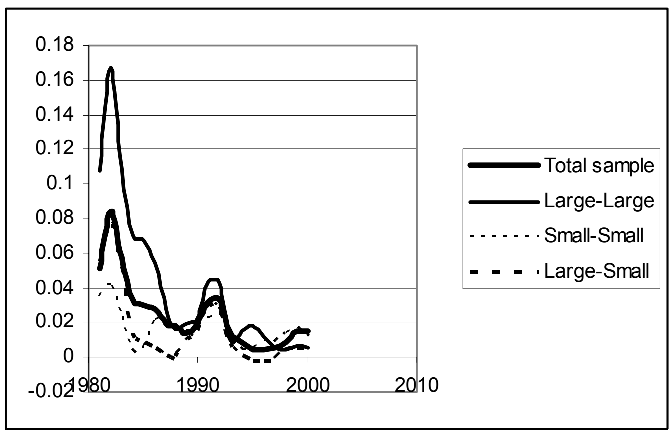
## Figure 6. Patterns of Correlations

This figure plots correlation patterns of real sales growth rate, return on asset (ROA), and stock return. Large-Large (Small-Small) indicates the average correlation patterns among the firms in the 1st quintile (5th quintile). Large-Small denotes the average correlation patterns between firms in the 1st quintile and firms in the 5th quintile.

(a) Real sales growth rate




(b) ROA




(c) Stock return

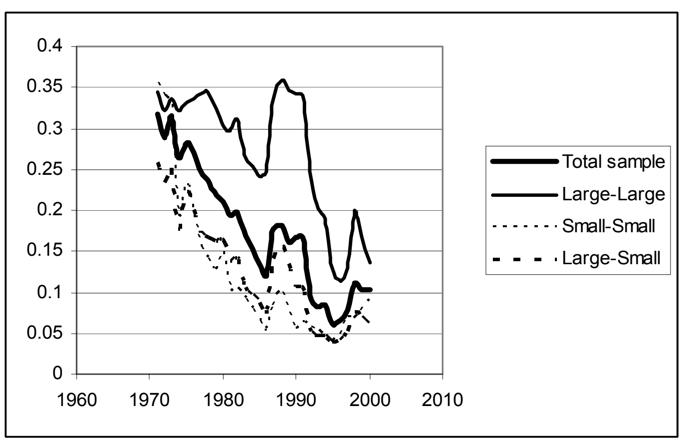
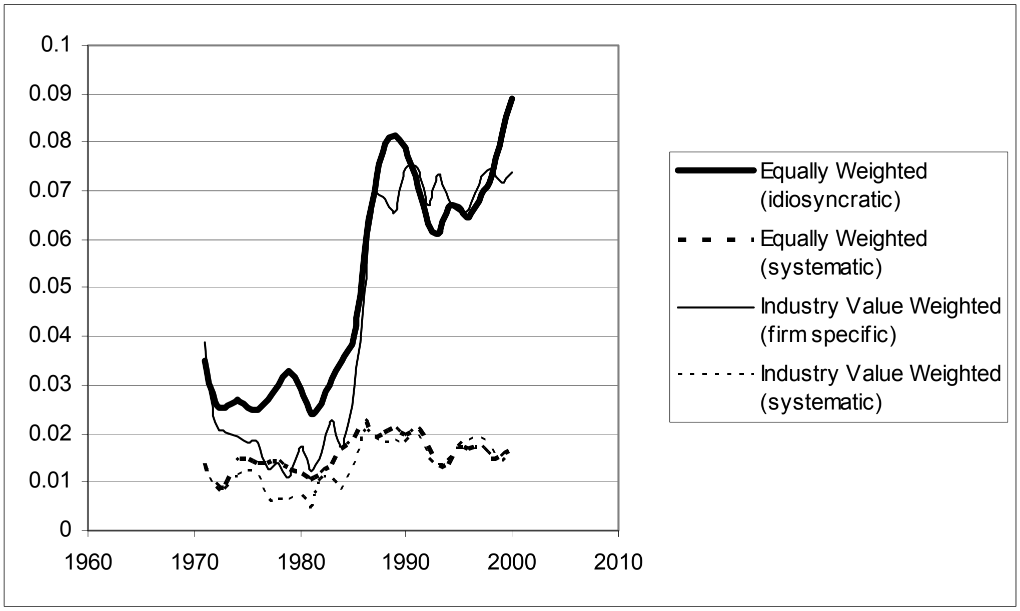


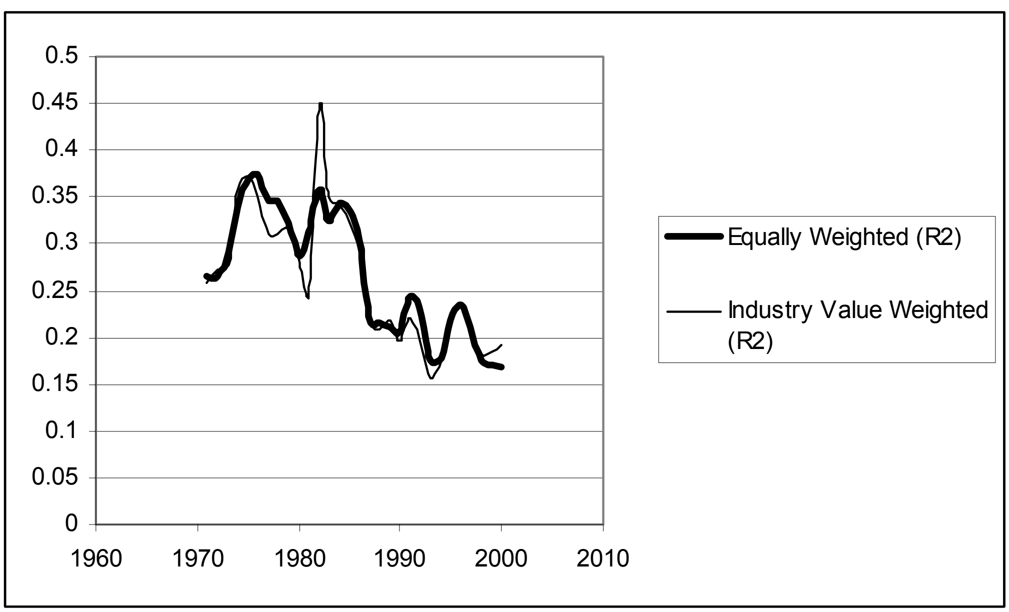
**Figure 7. Decomposed Volatilities: Idiosyncratic, Systematic, and $R^2$**
This figure plots the equal and value weighted (industry weight) averages of decomposed volatilities for each industry. For the value-weighted averages, we first calculate the equally weighted averages of decomposed volatilities of firms in each industry and then apply the industry weight to obtain the value-weighted averages.

**Panel A: Equally/value weighted average for sales growth rate**

(i) Firm-specific and systematic variations (real sales growth rate)

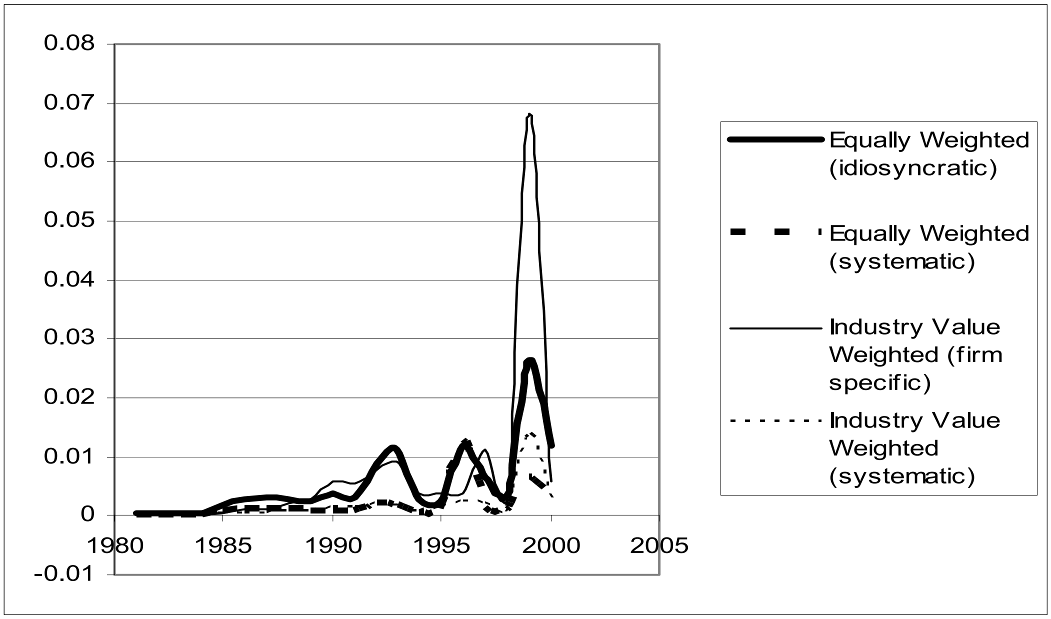



(ii) $R^2$ (real sales growth rate)



**Panel B: Equally/value weighted average for ROA**

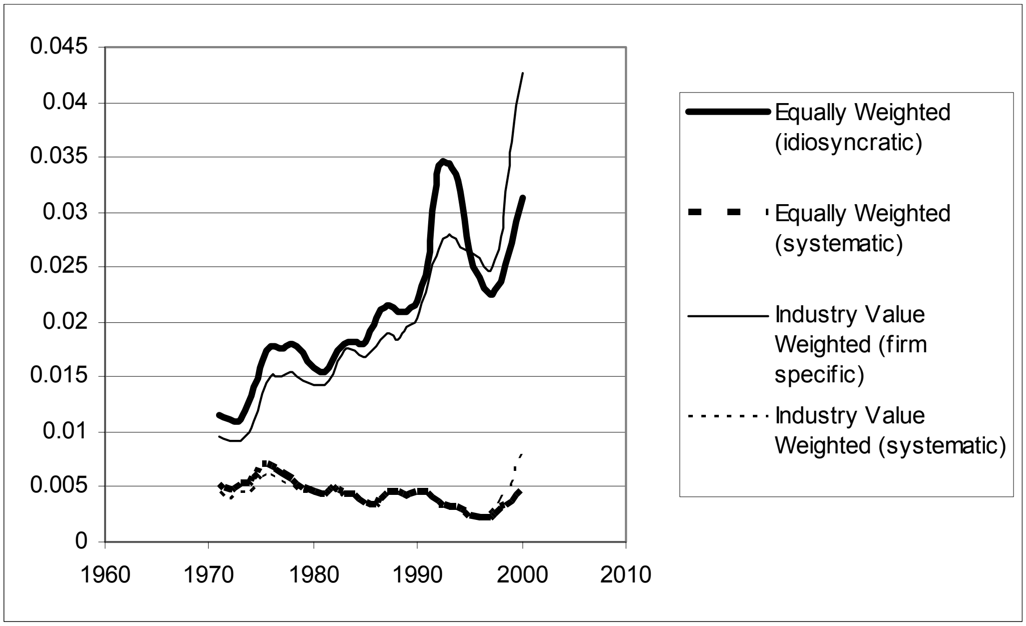
(i) Firm-specific and systematic variations (ROA)




(ii) $R^2$ (ROA)

**Panel C: Equally/value weighted average for stock return**

(i) Firm-specific and systematic variations (stock return)



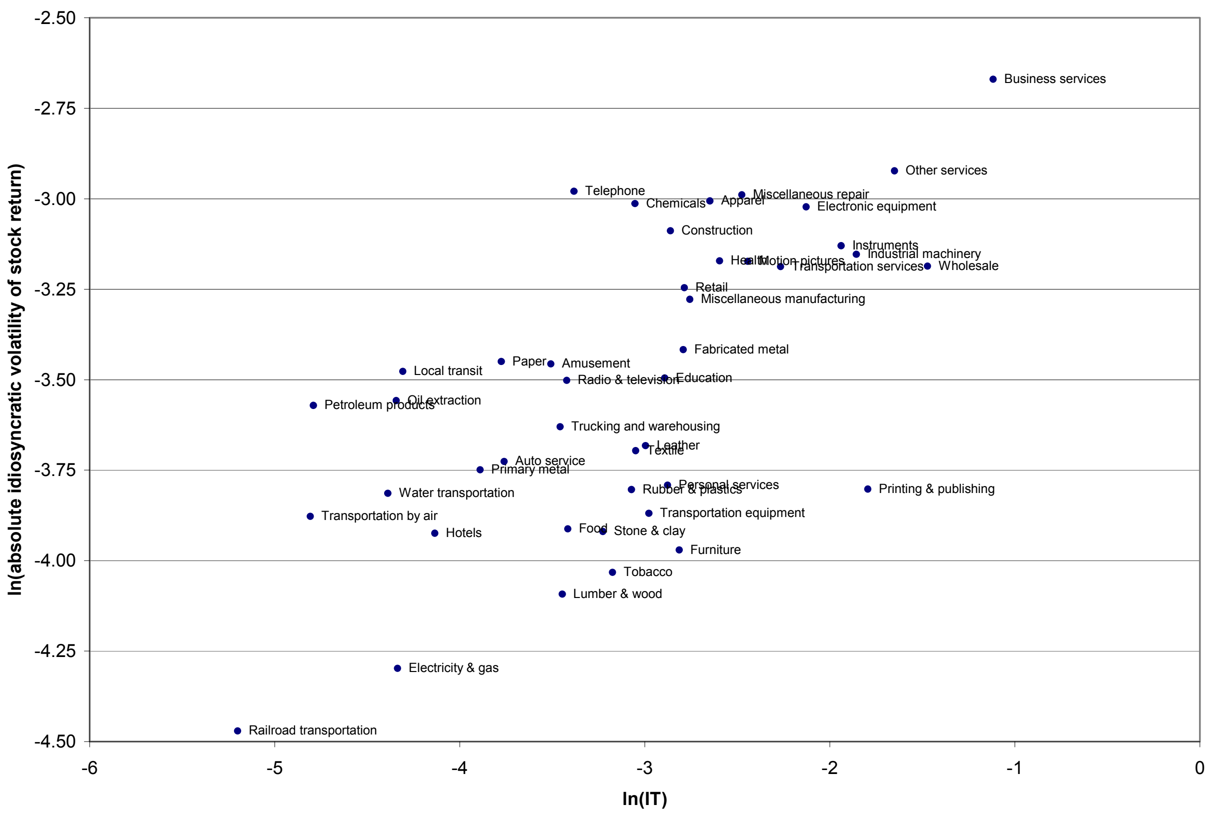

(ii) $R^2$ (stock return)

**Figure 8. IT Intensity and Idiosyncratic Volatilities in 2000**

The figures show the relationship between IT intensity and idiosyncratic volatility measures in 2000. Bivariate regression results in 2000 are also reported. Details on regression specification and sample restrictions are reported in Table 3. *t*-statistics are calculated from heteroskedastic-consistent standard errors.

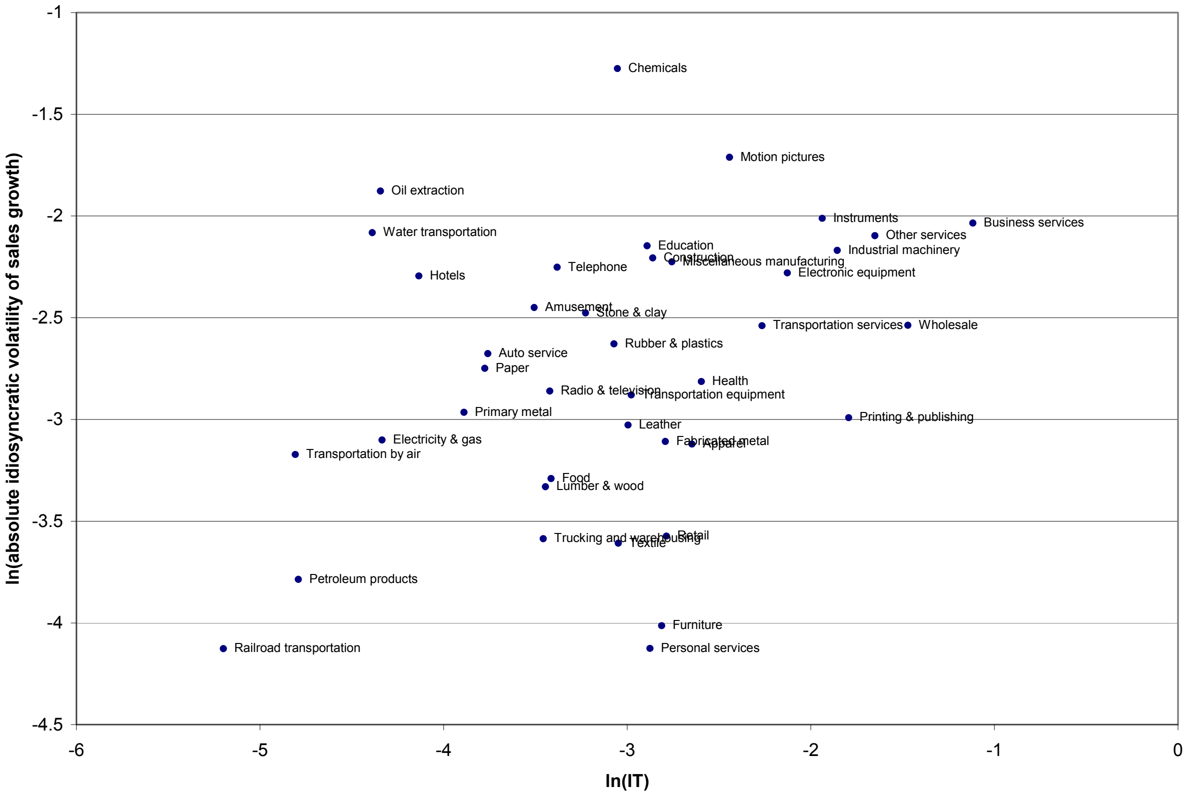
## Panel A: IT intensity and idiosyncratic volatility of stock return in 2000

*ln(idiosyncratic volatility of stock return) = -2.472 +0.273ln(IT)* *(t-stat=4.003)* *adjusted* $R^2 = 0.390$ *sample size=43*



## Panel B: IT intensity and idiosyncratic volatility of real sales growth in 2000

*ln(idiosyncratic volatility of sales growth) = -1.719 +0.340ln(IT)* *adjusted* $R^2$ *= 0.230*
*(t-stat=3.243)* *sample size=40*



**Panel C: IT intensity and idiosyncratic volatility of ROA in 2000**

*ln(idiosyncratic volatility of ROA) = -2.668 +1.168ln(IT)* *adjusted $R^2$ = 0.559*
*(t-stat=6.698)* *sample size=40*

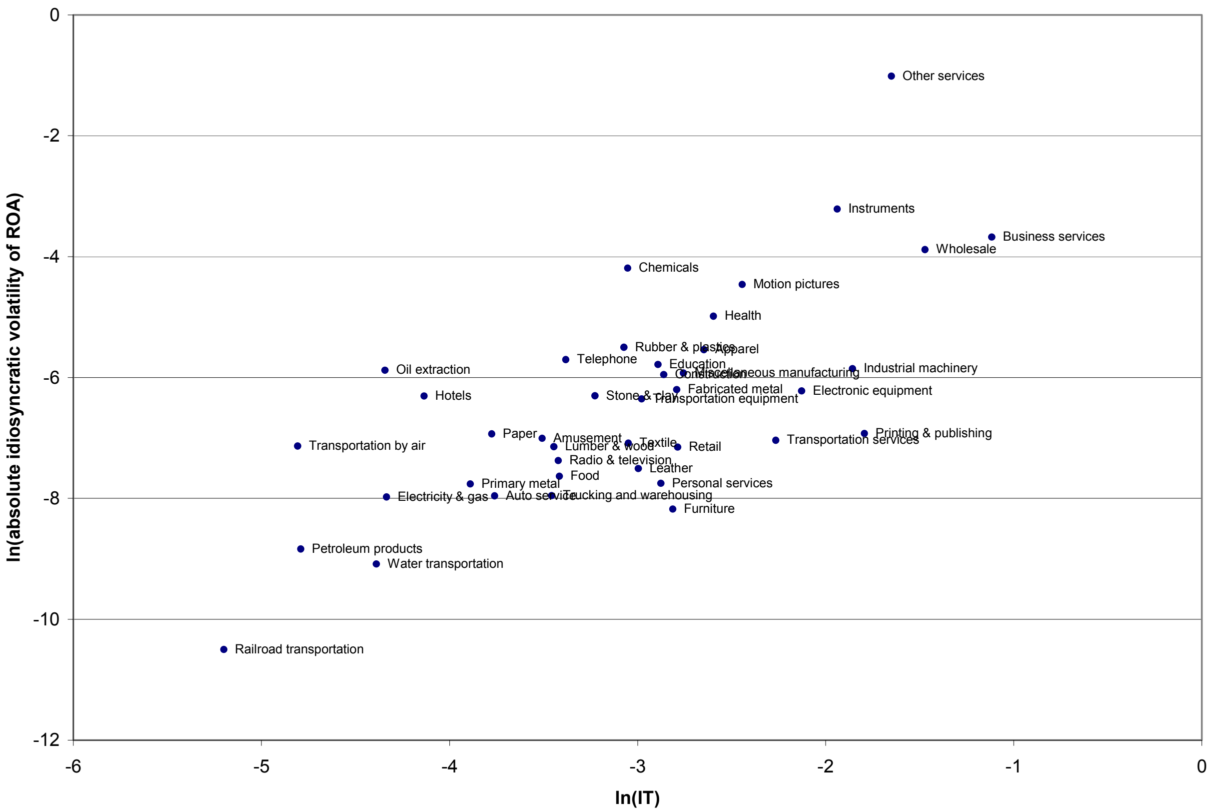


**Table 1. IT Intensity by Industry and by Year: 50 Industries and 1970, 1980, 1990, and 2000**

IT intensity is the ratio of IT capital to total capital in percentage. IT capital is defined as the sum of computers and software.

| Sector | Industry | IT intensity in nominal dollars | | | | IT intensity in 1994 real dollars | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1970 | 1980 | 1990 | 2000 | 1970 | 1980 | 1990 | 2000 |
| Agriculture (1-2) | 1 Farms | n.a. | n.a. | 0.061 | 0.347 | n.a. | n.a. | 0.042 | 0.666 |
| | 2 Agricultural services | n.a. | 0.293 | 0.137 | 0.124 | n.a. | 0.059 | 0.092 | 0.237 |
| Mining (3-6) | 3 Metal mining | n.a. | n.a. | 0.250 | 0.642 | n.a. | n.a. | 0.175 | 1.242 |
| | 4 Coal mining | n.a. | n.a. | 0.202 | 0.879 | n.a. | n.a. | 0.146 | 1.684 |
| | 5 Oil extraction | 0.174 | 0.509 | 0.370 | 0.776 | 0.010 | 0.174 | 0.286 | 1.733 |
| | 6 Nonmetallic minerals | n.a. | 0.041 | 0.409 | 1.504 | n.a. | 0.011 | 0.288 | 2.907 |
| Construction | 7 Construction | 0.607 | 0.271 | 0.840 | 4.031 | 0.036 | 0.073 | 0.591 | 7.381 |
| Manufacturing (8-27) | 8 Lumber & wood | 1.090 | 1.615 | 1.296 | 2.205 | 0.066 | 0.434 | 0.927 | 4.081 |
| Durables (8-17) | 9 Furniture | 1.120 | 1.836 | 2.954 | 4.443 | 0.075 | 0.535 | 2.182 | 7.915 |
| | 10 Stone & clay | 0.584 | 3.502 | 1.995 | 2.829 | 0.040 | 0.967 | 1.418 | 5.318 |
| | 11 Primary metal | 0.740 | 0.663 | 0.863 | 1.352 | 0.048 | 0.183 | 0.611 | 2.583 |
| | 12 Fabricated metal | 1.327 | 1.024 | 2.501 | 4.348 | 0.089 | 0.295 | 1.820 | 7.798 |
| | 13 Industrial machinery | 7.713 | 7.817 | 7.694 | 12.831 | 0.929 | 2.847 | 6.065 | 19.917 |
| | 14 Electronic equipment | 0.807 | 3.984 | 5.946 | 8.268 | 0.074 | 1.363 | 4.520 | 14.206 |
| | 15 Transportation equipment | 1.111 | 1.577 | 4.374 | 3.627 | 0.078 | 0.473 | 3.176 | 6.634 |
| | 16 Instruments | 2.558 | 2.486 | 8.106 | 11.459 | 0.217 | 0.849 | 6.394 | 17.646 |
| | 17 Miscellaneous manufacturing | 2.879 | 1.369 | 3.526 | 4.697 | 0.216 | 0.416 | 2.613 | 8.161 |
| Non-durables (18-27) | 18 Food | 0.925 | 0.752 | 1.765 | 2.250 | 0.061 | 0.209 | 1.265 | 4.252 |
| | 19 Tobacco | 2.229 | 1.352 | 3.020 | 2.339 | 0.162 | 0.404 | 2.263 | 4.203 |
| | 20 Textile | 1.211 | 0.517 | 1.506 | 3.262 | 0.076 | 0.144 | 1.104 | 5.790 |
| | 21 Apparel | 3.540 | 2.281 | 3.806 | 5.101 | 0.296 | 0.741 | 2.883 | 8.596 |
| | 22 Paper | 0.549 | 0.779 | 1.091 | 1.453 | 0.032 | 0.202 | 0.773 | 2.774 |
| | 23 Printing & publishing | 2.176 | 2.629 | 8.334 | 14.635 | 0.175 | 0.876 | 6.581 | 22.020 |
| | 24 Chemicals | 0.683 | 0.564 | 2.218 | 3.259 | 0.049 | 0.164 | 1.608 | 5.989 |
| | 25 Petroleum products | 0.732 | 0.797 | 0.760 | 0.451 | 0.044 | 0.212 | 0.542 | 0.891 |
| | 26 Rubber & plastics | 1.622 | 1.210 | 1.980 | 3.153 | 0.098 | 0.320 | 1.402 | 5.961 |
| | 27 Leather | 3.647 | 2.035 | 2.103 | 3.928 | 0.238 | 0.502 | 1.466 | 6.765 |

**Table 1. IT Intensity by Industry and by Year: 50 Industries and 1970, 1980, 1990, and 2000 [Continued]**

| Sector | Industry | IT intensity in nominal dollars | | | | IT intensity in 1994 real dollars | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1970 | 1980 | 1990 | 2000 | 1970 | 1980 | 1990 | 2000 |
| Transportation (28-34) | 28 Railroad transportation | 0.047 | 0.028 | 0.045 | 0.430 | 0.003 | 0.007 | 0.031 | 0.800 |
| | 29 Local transit | 0.442 | 0.246 | 0.395 | 1.037 | 0.037 | 0.072 | 0.281 | 1.987 |
| | 30 Trucking and warehousing | 0.384 | 0.118 | 0.451 | 2.009 | 0.023 | 0.028 | 0.309 | 3.587 |
| | 31 Water transportation | 0.644 | 0.126 | 0.151 | 0.823 | 0.040 | 0.034 | 0.109 | 1.541 |
| | 32 Transportation by air | 0.670 | 0.766 | 0.376 | 0.537 | 0.039 | 0.185 | 0.258 | 1.021 |
| | 33 Pipelines | 0.352 | 0.109 | 0.231 | 1.101 | 0.036 | 0.032 | 0.167 | 1.943 |
| | 34 Transportation services | 1.007 | 0.395 | 1.601 | 8.708 | 0.073 | 0.127 | 1.229 | 13.761 |
| Communication (35-36) | 35 Telephone | 0.210 | 0.266 | 1.584 | 2.536 | 0.020 | 0.087 | 1.188 | 4.156 |
| | 36 Radio & television | 0.630 | 0.706 | 0.630 | 2.436 | 0.043 | 0.215 | 0.468 | 4.136 |
| Utilities (37) | 37 Electricity & gas | 0.071 | 0.213 | 0.772 | 0.870 | 0.005 | 0.063 | 0.555 | 1.665 |
| Trade (38-39) | 38 Wholesale | 3.939 | 5.840 | 11.169 | 18.879 | 0.480 | 2.267 | 9.089 | 27.264 |
| | 39 Retail | 0.614 | 1.138 | 3.801 | 4.569 | 0.051 | 0.365 | 2.805 | 8.362 |
| Services (40-50) | 40 Hotels | 0.197 | 0.463 | 0.455 | 1.078 | 0.013 | 0.130 | 0.332 | 2.178 |
| | 41 Personal services | 0.413 | 1.216 | 2.201 | 4.321 | 0.035 | 0.372 | 1.622 | 7.606 |
| | 42 Business services | 2.579 | 8.280 | 29.380 | 28.941 | 0.409 | 4.346 | 24.254 | 41.404 |
| | 43 Auto service | 0.454 | 2.166 | 1.306 | 1.652 | 0.031 | 0.576 | 0.894 | 3.073 |
| | 44 Miscellaneous repair | 0.861 | 1.889 | 3.802 | 6.845 | 0.065 | 0.595 | 2.813 | 10.821 |
| | 45 Motion pictures | 0.765 | 2.867 | 3.518 | 5.581 | 0.078 | 0.900 | 2.634 | 9.689 |
| | 46 Amusement | 0.252 | 0.931 | 1.259 | 2.221 | 0.020 | 0.293 | 0.933 | 4.307 |
| | 47 Health | 0.959 | 1.113 | 4.267 | 5.477 | 0.081 | 0.360 | 3.194 | 9.607 |
| | 48 Legal | 9.613 | 4.318 | 14.430 | 21.950 | 1.227 | 1.707 | 11.880 | 30.150 |
| | 49 Education | 16.624 | 4.607 | 3.386 | 3.853 | 1.830 | 1.444 | 2.571 | 6.999 |
| | 50 Other services | 9.521 | 4.307 | 12.003 | 17.229 | 1.227 | 1.811 | 9.693 | 25.615 |
| | **Average (equally weighted)** | **1.984** | **1.745** | **3.725** | **5.523** | **0.199** | **0.606** | **2.571** | **7.981** |

**Table 2: Time-Series Patterns of Decomposed Volatility Series**

In panel A, we first calculate the ratio of absolute idiosyncratic volatility over absolute systematic volatility for each year for each industry. Then we calculate averages and medians for the whole sample and for each sub-period. In panel B, we calculate the correlations between absolute idiosyncratic volatility and absolute systematic volatility for each industry and then calculate averages and medians for the whole sample and for each sub-period.

**Panel A: The ratio of absolute idiosyncratic volatility to absolute systematic volatility**

| | | Stocks | Sales | ROA |
|---|---|---|---|---|
| Whole | mean | 5.965 | 4.857 | 7.1 |
| | median | 4.585 | 3.159 | 3.273 |
| | N | 1431 | 1388 | 920 |
| First Period | mean | 3.277 | 3.06 | 3.952 |
| (1971-1983) | median | 2.927 | 2.227 | 2.471 |
| (1981-1983 for ROA) | N | 609 | 566 | 128 |
| Second Period | mean | 7.957 | 6.095 | 7.61 |
| (1984-2000) | median | 6.584 | 3.895 | 3.38 |
| | N | 822 | 822 | 792 |

**Panel B: Correlations between absolute idiosyncratic and absolute systematic volatility**

| | | Stocks | Sales | ROA |
|---|---|---|---|---|
| Whole | mean | -0.013 | 0.558 | 0.712 |
| | median | -0.022 | 0.612 | 0.836 |
| | N | 49 | 49 | 49 |
| First Period | mean | 0.311 | 0.417 | 0.295 |
| (1971-1983) | median | 0.349 | 0.454 | 0.689 |
| (1981-1983 for ROA) | N | 48 | 45 | 42 |
| Second Period | mean | 0.164 | 0.48 | 0.703 |
| (1984-2000) | median | 0.203 | 0.536 | 0.814 |
| | N | 49 | 49 | 49 |

## Table 3. Fama-MacBeth Cross-Sectional Regression Results on Effects of IT on Volatilities (Bivariate Regression Analysis)

The model is estimated with WLS over a cross-section of industries for each year. All regressions are weighted by the industry share of market capitalization, sales, and total assets for stock return, sales, and ROA, respectively. Dependent variables are logarithms of absolute idiosyncratic, absolute systematic and relative idiosyncratic volatilities for stock return, real sales growth, and ROA. Relative idiosyncratic volatility is defined as the difference between logarithms of absolute idiosyncratic and absolute systematic volatilities. The sample period is 1971-2000 for stock return and sales and 1984-2000 for ROA. IT is the ratio of IT capital to total capital stock (all in 1994 real dollars). IT capital is defined as the sum of computers and software. In constructing volatility measures, firms with less than 30 monthly observations for stock return and firms with less than 15 quarterly observations for real sales growth and ROA, are excluded. The sample also excludes industries with less than five firms and industries whose IT capital is not defined. Average coefficients are calculated using Fama-MacBeth method. *t*-statistics are adjusted for autocorrelation and heteroskedasticity using the Newey-West method. Coefficient estimates of intercepts are not reported in the table. Coefficients significant at 10% or better are in boldface.

| Period | Volatility Measure | | Adjusted $R^2$ | Number of Industries | **ln(IT)** Estimate | Adj. t-stat |
|---|---|---|---|---|---|---|
| 1971-2000 | Stock | abs. idio. | 0.409 | 40.733 | **0.259**[a] | 12.891 |
| | Stock | abs. syst. | 0.215 | 40.733 | **0.156**[a] | 7.200 |
| | Stock | rel. idio. | 0.246 | 40.733 | **0.102**[a] | 7.249 |
| | Sales | abs. idio. | 0.213 | 36.500 | **0.274**[a] | 12.107 |
| | Sales | abs. syst. | 0.133 | 36.500 | **0.233**[a] | 6.560 |
| | Sales | rel. idio. | 0.030 | 36.500 | **0.040**[c] | 1.792 |
| 1971-1983 | Stock | abs. idio. | 0.477 | 39.769 | **0.268**[a] | 16.707 |
| | Stock | abs. syst. | 0.238 | 39.769 | **0.142**[a] | 12.668 |
| | Stock | rel. idio. | 0.340 | 39.769 | **0.126**[a] | 16.614 |
| | Sales | abs. idio. | 0.226 | 32.538 | **0.280**[a] | 24.633 |
| | Sales | abs. syst. | 0.183 | 32.538 | **0.295**[a] | 13.297 |
| | Sales | rel. idio. | -0.009 | 32.538 | -0.015 | -0.766 |
| 1984-2000 | Stock | abs. idio. | 0.357 | 41.471 | **0.251**[a] | 8.156 |
| | Stock | abs. syst. | 0.197 | 41.471 | **0.167**[a] | 4.801 |
| | Stock | rel. idio. | 0.175 | 41.471 | **0.084**[a] | 4.060 |
| | Sales | abs. idio. | 0.204 | 39.529 | **0.269**[a] | 6.957 |
| | Sales | abs. syst. | 0.094 | 39.529 | **0.186**[a] | 4.052 |
| | Sales | rel. idio. | 0.060 | 39.529 | **0.083**[a] | 7.856 |
| | ROA | abs. idio. | 0.319 | 36.647 | **0.751**[a] | 7.652 |
| | ROA | abs. syst. | 0.336 | 36.647 | **0.852**[a] | 13.490 |
| | ROA | rel. idio. | 0.038 | 36.647 | **-0.101**[b] | -2.369 |

[a]: Significant at 1 percent level.
[b]: Significant at 5 percent level.
[c]: Significant at 10 percent level.

## Table 4. Average Cross-Sectional Correlation Coefficients between Control Variables

Average cross-sectional correlation coefficients between variables are calculated for 1971-2000. IT is the ratio of IT capital to total capital stock (all in 1994 real dollars). Age is the average age of firms in an industry. (I/K) is the ratio of non-IT investment in year *t* to non-IT capital in year *t-1*. Book-to-market is the ratio of common equity to market capitalization of common stock. Advertising expenditure (ADV) and R&D capital stock (R&D) is scaled by property, plant, and equipment (PPE) (all in real dollars). Herfindahl-Hirschman index (HHI) variables are calculated using sales. Dispersion is the standard deviation of log of firm size (market capitalization) for each industry. Leverage is the sum of short-term and long-term debt divided by total assets. Liquidity is defined as the ratio of current assets to current liabilities. Foreign exposure is the ratio of foreign sales to total sales. Firm diversification is the average number of two-digit segments. Correlation coefficients related to foreign exposure and diversification are reported for 1989-1997. Numbers in parentheses are *p*-values. Coefficients significant at 10% or better are in boldface.

| | ln(IT) | ln(AGE) | I/K | Book-to-Market | ln(1+R&D) | ln(1+ADV) | HHI | Dispersion | Leverage | Liquidity | Foreign Exposure |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ln(AGE) | -0.170 | | | | | | | | | | |
| | (0.247) | | | | | | | | | | |
| I/K | **0.331** | **-0.273** | | | | | | | | | |
| | **(0.014)** | **(0.048)** | | | | | | | | | |
| Book-to-Market | **-0.290** | **0.250** | **-0.346** | | | | | | | | |
| | **(0.039)** | **(0.073)** | **(0.009)** | | | | | | | | |
| ln(1+R&D) | **0.504** | -0.143 | 0.140 | **-0.276** | | | | | | | |
| | **(0.000)** | (0.318) | (0.326) | **(0.044)** | | | | | | | |
| ln(1+ADV) | **0.347** | 0.016 | -0.009 | -0.173 | 0.154 | | | | | | |
| | **(0.011)** | (0.913) | (0.951) | (0.224) | (0.277) | | | | | | |
| HHI | -0.189 | **-0.403** | -0.002 | 0.016 | -0.102 | -0.038 | | | | | |
| | (0.190) | **(0.002)** | (0.989) | (0.912) | (0.477) | (0.794) | | | | | |
| Dispersion | -0.146 | **0.266** | -0.047 | -0.220 | -0.026 | -0.067 | -0.058 | | | | |
| | (0.323) | **(0.055)** | (0.747) | (0.118) | (0.857) | (0.646) | (0.688) | | | | |
| Leverage | -0.202 | -0.205 | 0.127 | 0.027 | **-0.319** | -0.224 | 0.099 | -0.145 | | | |
| | (0.160) | (0.147) | (0.373) | (0.850) | **(0.017)** | (0.107) | (0.491) | (0.312) | | | |
| Liquidity | **0.285** | -0.009 | -0.177 | -0.018 | 0.155 | **0.403** | 0.135 | -0.200 | **-0.478** | | |
| | **(0.042)** | (0.949) | (0.209) | (0.901) | (0.275) | **(0.002)** | (0.344) | (0.156) | **(0.000)** | | |
| Foreign Exposure | 0.109 | 0.055 | -0.069 | -0.164 | **0.383** | 0.087 | 0.196 | **0.338** | **-0.296** | 0.127 | |
| | (0.461) | (0.709) | (0.637) | (0.254) | **(0.004)** | (0.550) | (0.170) | **(0.013)** | **(0.032)** | (0.380) | |
| Diversification | **-0.280** | **0.531** | -0.144 | 0.103 | -0.201 | -0.119 | 0.169 | **0.419** | **-0.252** | -0.068 | **0.325** |
| | **(0.041)** | **(0.000)** | (0.307) | (0.470) | (0.149) | (0.404) | (0.228) | **(0.001)** | **(0.066)** | (0.636) | **(0.017)** |

**Table 5. Fama-MacBeth Cross-Sectional Regression Results on Effects of IT on Volatilities (Multivariate Regression Analysis)**

The model is estimated with WLS over a cross-section of industries for each year. All regressions are weighted by the industry share of market capitalization, sales, and total assets for stock return, sales, and ROA, respectively. Dependent variables are logarithms of absolute idiosyncratic, absolute systematic and relative idiosyncratic volatilities for stock return, real sales growth, and ROA. Relative idiosyncratic volatility is defined as the difference between logarithms of absolute idiosyncratic and absolute systematic volatilities. In constructing volatility measures, firms with less than 30 monthly observations for stock return and firms with less than 15 quarterly observations for real sales growth and ROA, are excluded. The sample also excludes industries with less than five firms and industries whose IT capital is not defined. IT is the ratio of IT capital to total capital stock (all in 1994 real dollars). Age is the average age of firms in an industry. (I/K) is the ratio of non-IT investment in year *t* to non-IT capital in year *t-1*. Book-to-market is the ratio of common equity to market capitalization of common stock. Advertising expenditure (ADV) and R&D capital stock (R&D) is scaled by property, plant, and equipment (PPE) (all in real dollars). Herfindahl-Hirschman index (HHI) variables are calculated using sales. Dispersion (DIS) is the standard deviation of log of firm size (market capitalization, sales, and total assets). Leverage (LEV) is the sum of short-term and long-term debt divided by total assets. Liquidity (LIQ) is defined as the ratio of current assets to current liabilities. Average coefficients are calculated using Fama-MacBeth method. *t*-statistics are adjusted for autocorrelation and heteroskedasticity using the Newey-West method. Coefficient estimates of intercepts are not reported in the table. Coefficients significant at 10% or better are in boldface.

| Period | Volatility Measure | | Adj. $R^2$ | No. of Industries. | ln(IT) | ln(AGE) | I/K | BM | ln(1+ R&D) | ln(1+ ADV) | HHI | DIS | LEV | LIQ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1971-2000 | Stock | abs. idio. | 0.804 | 40.733 | **0.061[a]** | **-0.811[a]** | 0.173 | 0.243 | 0.036 | -0.210 | 0.344 | **0.210[b]** | **-1.444[a]** | **0.201[a]** |
| | Stock | abs. syst. | 0.711 | 40.733 | **-0.030[b]** | **-0.754[a]** | **1.494[b]** | **0.552[a]** | 0.178 | **-1.317[c]** | **-0.667[a]** | **0.219[a]** | **-1.982[a]** | **0.195[c]** |
| | Stock | rel. idio. | 0.588 | 40.733 | **0.091[a]** | -0.057 | **-1.321[b]** | **-0.310[c]** | -0.141 | **1.107[b]** | **1.011[a]** | -0.009 | 0.538 | 0.006 |
| | Sales | abs. idio. | 0.549 | 36.500 | **0.105[a]** | **-0.267[c]** | **2.788[c]** | **1.348[a]** | **1.048[a]** | 0.639 | -0.428 | **0.353[a]** | -1.689 | 0.162 |
| | Sales | abs. syst. | 0.578 | 36.500 | 0.032 | -0.212 | 3.233 | **1.041[a]** | **1.045[b]** | **-3.132[a]** | -0.552 | **0.290[a]** | **-1.641[b]** | **0.529[a]** |
| | Sales | rel. idio. | 0.364 | 36.500 | **0.074[a]** | -0.055 | -0.445 | 0.307 | 0.003 | **3.771[a]** | 0.124 | 0.063 | -0.048 | **-0.367[a]** |
| 1971-1983 | Stock | abs. idio. | 0.797 | 39.769 | **0.063[a]** | **-0.714[a]** | 1.069 | **0.424[a]** | **-0.333[c]** | -0.464 | **-0.129[a]** | 0.100 | **-2.687[a]** | **0.188[a]** |
| | Stock | abs. syst. | 0.670 | 39.769 | -0.015 | **-0.681[a]** | 1.936 | **0.484[a]** | **-0.012** | -0.972 | **-0.852[a]** | 0.006 | **-2.774[a]** | -0.076 |
| | Stock | rel. idio. | 0.688 | 39.769 | **0.078[a]** | -0.034 | -0.867 | -0.059 | -0.321 | 0.508 | **0.724[a]** | 0.095 | 0.087 | **0.264[a]** |
| | Sales | abs. idio. | 0.494 | 32.538 | **0.104[b]** | -0.283 | **5.802[a]** | **1.355[a]** | **1.213[b]** | -0.208 | **-3.859[a]** | **0.204[b]** | **-3.780[a]** | -0.139 |
| | Sales | abs. syst. | 0.600 | 32.538 | 0.060 | 0.082 | **8.806[a]** | **1.330[a]** | **1.543[b]** | **-5.785[a]** | **-4.583[a]** | **0.181[a]** | **-3.172[a]** | **0.391[a]** |
| | Sales | rel. idio. | 0.339 | 32.538 | **0.044[b]** | **-0.365[b]** | **-3.004[a]** | 0.026 | -0.330 | **5.577[b]** | **0.723[a]** | 0.023 | -0.608 | **-0.530[b]** |
| 1984-2000 | Stock | abs. idio. | 0.809 | 41.471 | **0.059[b]** | **-0.885[a]** | -0.511 | 0.104 | **0.319[b]** | -0.016 | **0.705[b]** | **0.294[b]** | -0.493 | **0.210[c]** |
| | Stock | abs. syst. | 0.743 | 41.471 | **-0.041[a]** | **-0.811[a]** | 1.157 | **0.604[a]** | **0.323[a]** | **-1.581[c]** | **-0.525[a]** | **0.382[a]** | **-1.376[a]** | **0.402[a]** |
| | Stock | rel. idio. | 0.512 | 41.471 | **0.101[a]** | -0.074 | **-1.668[c]** | **-0.501[b]** | -0.004 | **1.565[a]** | **1.230[a]** | -0.087 | **0.883[c]** | -0.191 |
| | Sales | abs. idio. | 0.591 | 39.529 | **0.106[a]** | **-0.254[c]** | 0.483 | **1.343[a]** | **0.922[a]** | **1.286[a]** | **2.196[c]** | **0.466[a]** | -0.090 | **0.393[a]** |
| | Sales | abs. syst. | 0.562 | 39.529 | 0.010 | **-0.438[a]** | -1.029 | **0.820[c]** | 0.664[c] | **-1.104[a]** | **2.530[c]** | **0.373[a]** | -0.471 | **0.635[a]** |
| | Sales | rel. idio. | 0.383 | 39.529 | **0.096[a]** | **0.183[b]** | 1.512 | 0.523 | 0.258 | **2.390[a]** | -0.334 | **0.093[c]** | 0.381 | **-0.242[a]** |
| | ROA | abs. idio. | 0.532 | 36.647 | **0.127[b]** | -0.214 | -1.415 | **-1.869[b]** | **3.344[a]** | **-3.306[a]** | -1.721 | **0.539[c]** | **3.024[b]** | **1.255[a]** |
| | ROA | abs. syst. | 0.587 | 36.647 | 0.128 | **-0.711[b]** | 1.057 | **-2.049[c]** | **2.203[a]** | **-4.289[a]** | **-3.217[b]** | **0.430[c]** | 1.593 | **1.903[a]** |
| | ROA | rel. idio. | 0.528 | 36.647 | -0.001 | **0.497[b]** | -2.472 | 0.180 | **1.141[b]** | 0.983 | 1.496 | 0.109 | **1.430[b]** | **-0.649[b]** |

[a]: Significant at 1 percent level. [b]: Significant at 5 percent level. [c]: Significant at 10 percent level.

**Table 6. Fama-MacBeth Cross-Sectional Regression Results on Effects of IT on Volatilities: Foreign Exposure and Diversification**

The model is estimated with WLS over a cross-section of industries for each year. All regressions are weighted by the industry share of market capitalization, sales, and total assets for stock return, sales, and ROA, respectively. Dependent variables are logarithms of absolute idiosyncratic, absolute systematic and relative idiosyncratic volatilities for stock return, real sales growth, and ROA. Relative idiosyncratic volatility is defined as the difference between logarithms of absolute idiosyncratic and absolute systematic volatilities. In constructing volatility measures, firms with less than 30 monthly observations for stock return and firms with less than 15 quarterly observations for real sales growth and ROA, are excluded. The sample also excludes industries with less than five firms and industries whose IT capital is not defined. Foreign Exposure (FE) is defined as the ratio of foreign sales to the sum of domestic and foreign sales. Firm diversification (SEG) is the average number of two-digit segments. Since geographic and business segment information in COMPUSTAT is available from 1985 and has a significant change in the FASB segment reporting standards in 1998 and we construct 5-year average of the variables, the sample period is restricted to 1989-1997. Average coefficients are calculated using Fama-MacBeth method. *t*-statistics are adjusted for autocorrelation and heteroskedasticity using the Newey-West method. Coefficient estimates of intercepts are not reported in the table. Coefficients significant at 10% or better are in boldface.

| Volatility Measure | Adj. $R^2$ | No. of Inds. | **ln(IT)** | **ln(AGE)** | **I/K** | **BM** | **ln(1+ R&D)** | **ln(1+ ADV)** | **HHI** | **DIS** | **LEV** | **LIQ** | **FE** | **SEG** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock abs. idio. | 0.836 | 39.889 | **0.090**[a] | **-0.946**[a] | **-2.451**[a] | **0.286**[c] | **-0.026**[a] | -0.109 | **1.088**[a] | **0.195**[b] | -0.021 | 0.085 | **0.906**[a] | -0.176 |
| Stock abs. syst. | 0.765 | 39.889 | **-0.036**[a] | -0.889 | 0.748 | **0.896**[a] | **0.048**[a] | **-1.200**[c] | **-1.154**[a] | **0.305**[a] | -0.423 | **0.443**[a] | **0.646**[a] | -0.040 |
| Stock rel. idio. | 0.592 | 39.889 | **0.126**[a] | **-0.056**[a] | **-3.200**[a] | **-0.610**[b] | -0.074 | **1.090**[c] | **2.242**[a] | **-0.110**[a] | **0.402**[a] | **-0.358**[a] | 0.260 | -0.137 |
| Sales abs. idio. | 0.716 | 39.667 | **0.123**[b] | **-1.018**[b] | **-2.953**[b] | **1.823**[a] | **-0.505**[a] | **0.946**[a] | -0.109 | **0.379**[a] | **0.662**[a] | **0.067**[c] | **2.778**[a] | 0.137 |
| Sales abs. syst. | 0.690 | 39.667 | 0.024 | **-1.260**[c] | **-3.507**[c] | **1.669**[a] | **-0.274**[a] | -0.094 | 0.766 | **0.398**[a] | 0.529 | **0.384**[a] | **1.799**[a] | **0.505**[a] |
| Sales rel. idio. | 0.422 | 39.667 | **0.098**[a] | 0.241 | 0.554 | 0.154 | **-0.231**[a] | **1.040**[b] | **-0.875**[c] | -0.019 | 0.133 | **-0.317**[a] | **0.978**[b] | **-0.367**[b] |
| ROA abs. idio. | 0.583 | 36.556 | **0.144**[b] | 0.534 | -0.151 | -0.383 | 0.954 | **-7.645**[a] | **-2.445**[a] | **1.344**[a] | -0.326 | **1.486**[a] | **3.511**[b] | **-2.553**[a] |
| ROA abs. syst. | 0.642 | 36.556 | 0.127 | -0.363 | -0.517 | -0.416 | 0.294 | **-6.305**[b] | **-3.047**[a] | **1.165**[a] | -0.073 | **2.129**[a] | **3.611**[a] | -2.191[a] |
| ROA rel. idio. | 0.538 | 36.556 | 0.017 | 0.897 | 0.366 | 0.034 | **0.660**[a] | **-1.340**[b] | 0.602 | **0.179**[c] | -0.252 | -0.644 | -0.100 | -0.361 |

[a]: Significant at 1 percent level.
[b]: Significant at 5 percent level.
[c]: Significant at 10 percent level.

## Table 7. Fama-MacBeth Cross-Sectional Regression Results on Volatility Growth and IT

In this table, we test whether industries with high IT intensity exhibit faster volatility growth. Dependent variables are 5 year log difference in each volatility measure between year t and t+5. Independent variables are ln(IT) and ln(VOL). ln(IT) is log of IT intensity in year *t* for each industry and ln(VOL) is log of volatility measure in year t. The model is estimated with WLS over a cross-section of industries for each year. All regressions are weighted by the industry share of market capitalization, sales, and total assets for stock return, sales, and ROA, respectively. In constructing volatility measures, firms with less than 30 monthly observations for stock return and firms with less than 15 quarterly observations for real sales growth and ROA, are excluded. The sample also excludes industries with less than five firms and industries whose IT capital is not defined. Average coefficients are calculated using Fama-MacBeth method. *t*-statistics are adjusted for autocorrelation and heteroskedasticity using the Newey-West method. Coefficient estimates of intercepts are not reported in the table. Coefficients significant at 10% or better are in boldface.

| (t+*1*) Period | Volatility | Measure | Adjusted $R^2$ | Number of Industries | **ln(IT)** Estimate | Adj. t-stat | **ln(VOL)** Estimate | Adj. t-stat |
|---|---|---|---|---|---|---|---|---|
| 1976-2000 | Stock | abs. idio. | 0.215 | 41.240 | 0.039 | 1.666 | **-0.224**[a] | -3.783 |
| | Stock | abs. syst. | 0.173 | 41.240 | **0.041**[a] | 4.883 | **-0.256**[a] | -4.961 |
| | Stock | rel. idio. | 0.376 | 41.240 | **0.060**[a] | 5.077 | **-0.738**[a] | -10.286 |
| | Sales | abs. idio. | 0.227 | 37.680 | **0.110**[a] | 5.120 | **-0.388**[a] | -7.495 |
| | Sales | abs. syst. | 0.289 | 37.680 | **0.106**[a] | 4.107 | **-0.490**[a] | -9.788 |
| | Sales | rel. idio. | 0.449 | 37.680 | **0.042**[b] | 2.441 | **-0.892**[a] | -15.791 |
| 1976-1983 | Stock | abs. idio. | 0.218 | 40.750 | 0.006 | 0.154 | **-0.149**[c] | -1.906 |
| | Stock | abs. syst. | 0.112 | 40.750 | **0.028**[a] | 4.225 | **-0.300**[a] | -18.609 |
| | Stock | rel. idio. | 0.405 | 40.750 | **0.092**[a] | 20.965 | **-0.829**[a] | -9.297 |
| | Sales | abs. idio. | 0.295 | 33.875 | **0.082**[a] | 23.033 | **-0.406**[a] | -13.224 |
| | Sales | abs. syst. | 0.247 | 33.875 | **0.078**[a] | 3.925 | **-0.398**[a] | -6.099 |
| | Sales | rel. idio. | 0.390 | 33.875 | -0.012 | -1.485 | **-0.820**[a] | -21.387 |
| 1984-2000 | Stock | abs. idio. | 0.214 | 41.471 | **0.055**[b] | 2.498 | **-0.259**[b] | -3.395 |
| | Stock | abs. syst. | 0.202 | 41.471 | **0.048**[a] | 5.243 | **-0.235**[b] | -3.224 |
| | Stock | rel. idio. | 0.362 | 41.471 | **0.045**[a] | 3.445 | **-0.695**[a] | -8.634 |
| | Sales | abs. idio. | 0.195 | 39.471 | **0.123**[a] | 4.157 | **-0.379**[a] | -5.091 |
| | Sales | abs. syst. | 0.309 | 39.471 | **0.119**[a] | 3.512 | **-0.534**[a] | -10.336 |
| | Sales | rel. idio. | 0.477 | 39.471 | **0.068**[a] | 7.555 | **-0.925**[a] | -12.174 |
| (ROA) 1986-2000 | ROA | abs. idio. | 0.221 | 37.333 | **0.424**[a] | 15.333 | **-0.452**[a] | -8.108 |
| | ROA | abs. syst. | 0.209 | 37.333 | **0.371**[a] | 6.410 | **-0.374**[a] | -8.250 |
| | ROA | rel. idio. | 0.384 | 37.333 | -0.028 | -0.491 | **-0.700**[a] | -11.312 |

[a]: Significant at 1 percent level

[b]: Significant at 5 percent level.

[c]: Significant at 10 percent level.