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Information Technology, Creative Destruction, and Firm-Specific Volatility

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Abstract

We investigate underlying factors that explain increases in the firm-specific volatilities of stock returns and fundamentals. We find that firm-specific volatilities are significantly higher in both manufacturing and non-manufacturing industries that are more information technology (IT) intensive. 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. Our findings are consistent with rising firm-specific volatility in U.S. stocks reflecting an accelerating pace of creative destruction; and with greater firm-specific volatility in richer and faster growing countries reflecting more intensive creative destruction in those economies.

Keywords: Information Technology, Firm-Specific Volatility, Creative Destruction

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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.

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).[1]

In contrast, the volatilities of firm-level performance measures rose sharply over the same period. Figure 1 shows this intriguing divergence between aggregate (macro) and firm-level (micro) volatilities. Figure 1 contrasts the aggregate volatilities of stock return, sales growth, and return on assets (ROA) with the average volatilities of firm-level stock returns, sales growth rates, and ROAs.[2] All the firm-level volatilities trend upward from 1971 through 2000, while the aggregate volatilities trend down or hold steady.

[1] 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 G-7 countries have not become more synchronized despite large increases in international trade and financial integration.

[Insert Figure 1 Here]

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 financial (stock return) and real (sales growth rate and ROA) terms. In other words, firm-specific (idiosyncratic) volatilities rose faster than industry- or economy-wide (systematic) volatilities over the sample period.[3]

In this paper, we propose that creative destruction associated with the rapid diffusion of *information technology* (IT) into most sectors of the U.S. economy plays a major role in the aforementioned divergence. Creative destruction, Schumpeter's (1912) theory that economic growth arises from creative firms adopting new technology, thereby destroying stagnant firms, necessarily implies winners and losers. We propose that the incorporation of IT in existing 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 workers and appropriate organizational forms. In a similar vein, Hayek (1941)

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[2] Details on the construction of the three variables and corresponding volatility measures are provided in Section III.

[3] 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.

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 products, they could attract diverse pools of consumers, generating yet more heterogeneous performance among firms within the industry.[4]

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

[Insert Figure 2 Here]

IT investment (computers, software, and related assets) rose 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.[5] Reflecting the increase in IT investment, aggregate IT intensity (the ratio of IT capital to total capital) also rose sharply. Figure 2(a) shows the time-series pattern of aggregate IT intensity (in 1994 real dollars) from 1971 to 2000.[6] Figure 2(b) shows that, despite declining somewhat over time, substantial

[4] Section I fully discusses the two channels how IT could affect firm-specific volatility.
[5] U.S. firms invested $180 billion in Research and Development (R&D), excluding federally funded R&D. This is about the two-thirds of their IT investment.
[6] Details on the construction and characteristics of the IT intensity are provided in Section II.

cross-industry variation in IT intensity persists through 2000.[7, 8] 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 for other industry characteristics that might affect volatility, such as average firm age, non-IT capital investment, a Herfindahl-Hirschman Index, leverage, liquidity, a firm size distribution measure, foreign exposure, firm diversification, and measures of intangibles such as research and development (R&D), advertising, and a book-to-market ratio. We also find that the growth rate of firm-specific 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.

First, our study identifies an underlying factor behind the recent increase in firm-specific volatility in the U.S. individual stock returns found by Morck *et al.* (2000) and Campbell *et al.* (2001). We find that the firm-specific volatility of fundamentals exhibits a similar increase, and that cross-sectional patterns in both are well explained by corresponding patterns in IT intensity. We speculate that some firms are more successful than others in adopting IT, and that this accentuates firm-specific performance differences. That is, rising firm-specific volatility indicates a growing divergence of

[7] Time-series patterns of IT intensity 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 relationship between IT intensity and volatility.

[8] Jovanovic and Rousseau (2003) find that the recent diffusion of IT across industries was slower than that of electrification in the early twentieth century. From 1960 through 2001, cross-industry variation in IT

winners from losers, and so might be a sign of intensifying creative destruction in the U.S. economy.

This extends other recent work on firm-specific returns volatility. Irvine and Pontiff (2004) and Wei and Zhang (2004) show that changes in stock return volatility track changes in earnings volatility. This suggests that real economic factors cannot be ignored in explaining the rising firm-specific returns volatility in U.S. stocks. We concur, but take this argument a step further by exploring and testing a detailed economic explanation of why firm-specific fundamentals volatility rose.[9]

Second, our findings illuminate relationships between volatility and several other important economic variables. Morck *et al.* (2000) and Durnev *et al.* (2004b) find higher firm-specific volatility related to higher real GDP *per capita* and faster economic growth, respectively. He *et al.* (2004) link faster GDP and productivity growth to an increased turnover in 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 if creative destruction induces firm-specific volatility that averages out in aggregate measures. This is consistent with more intensive creative destruction underlying faster and more sustained economic growth, as in

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intensity declined, but remains substantial – even in the latter part of the period. Details on the distribution of IT intensity across industries are provided in Section II.

[9] Focusing on stock return volatility, Xu and Malkiel (2003) link higher firm-specific volatility to institutional holdings and long-term earnings growth forecasts. Using the market model, Dennis and Strickland (2004) also link institutional ownership, firm diversification, and leverage to firm-specific stock return volatility. More directly relevant to our findings, Agarwal *et al.* (2004) find that when 'bricks and mortar' firms enter eCommerce, firm-specific volatility increases, though only after June 1998, when they

Schumpeter (1912) and the *new endogenous growth theory* summarized in e.g., Aghion and Howitt (1998).[10]

Greater firm-specific volatility is also 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.*, 2004a; Huang, 2004; Jin and Myers, 2004; Ozoguz, 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 volatility. For example, Jin and Myers (2004) link greater firm-specific fundamentals and returns volatility to better institutions preventing corporate insiders and officials from confiscating firm-specific abnormal profits, and present convincing evidence of such a link. Their view is also consistent with much other work, and ought to be regarded as a complement to ours, rather than an alternative theory. For example, greater transparency might allow better financing terms for innovators, and hence faster creative destruction.

A third insight is that IT researchers might investigate second moments. The

suggest the Internet reached a critical size threshold.

[10] 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.

existing IT literature has uncovered important results using 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.[11] Using a growth accounting framework, Oliner and Sichel (2000) and Jorgenson (2001) show that the growth in IT capital stock accounts for nearly half of the rise in U.S. productivity growth from the early to late 1990s. Brynjolfsson and Hitt (2003) find similar results at the firm-level. However, research linking IT with second moments as well as first moments is sparse, and many interesting questions remain open. We are actively pursuing this in a follow-up paper.

A fourth insight challenges 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 volatility is not the simple sum of firm volatilities

The paper is structured as follows. Section I examines how IT can affect firm-specific volatility. Section II describes the construction and characteristics of our industry-level IT variable. Section III examines the characteristics of firm-level volatility, and the changes in correlation patterns of stock returns, sales growth rates, and ROAs. Section IV explains our decomposition of total volatility into firm-specific and systematic

[11] 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 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.

components. Section V discusses regression results, and Section VI concludes.

I. Information Technology, Firm-Specific Volatility, and Alternative Hypotheses

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

A. IT and Firm-Specific Volatility

Information Technology is often considered an example of *general purpose technology* (GPT), which Helpman and Trajtenberg (1998), Jovanovic and Rousseau (2003), and others define as a technology that transforms the way firms conduct business.[12] 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 become more volatile and heterogeneous; that is, to exhibit greater firm-specific volatility.

First channel: IT increases firm-level heterogeneity by permitting improvements in existing production processes and the undertaking of 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) stress skilled workers and firm organization, while Hayek (1941) focuses on managerial foresight. Firms with more complementary assets gain the most from IT.[13] 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) 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.[14] If older firms are larger, this implies that heterogeneity between small and large firms should increase as IT is adopted. Consistent with this line of argument, we find that correlations between large and small firm performance decline over time in the U.S.[15] 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.

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

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

[14] Similarly, Laitner and Stolyarov (2003) suggest that new information technologies render old knowledge and physical capital obsolete, thereby reducing the market value of physical capital.

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 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.[16] Brynjolfsson and Hitt (2003) survey Fortune 500 information system managers in 1997 and report the top five reasons for IT investment: 1) improving customer services, 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 a small, moderate, or great effect on cost reduction and quality improvement. About 80% of respondents replied that IT has at least a moderate

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[15] Correlation patterns are discussed in Section III.

[16] This is more unique to IT as a GPT. For example, electricity does not obviously deepen the uniqueness of products.

effect (about 40% for a great effect) *on both*.[17]

B. Firm-Specific 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 some control variables are in Appendix I.

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.[18] 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.[19] Intense price competition might thus amplify firm-specific volatility.[20]

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[17] 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 to 10M, 10 to 25M, 25 to 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 between IT and R&D are discussed in Appendix II.

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

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

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.[21] To measure the intensity of price competition in each industry, we calculate a sales-based Herfindahl-Hirschman Index for each industry in each year.

Distribution of Firm Size

The distribution of firm size may reflect pre-existing heterogeneity among firms, which could affect volatility.[22] 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.[23] 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. We construct the

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[20] 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 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.

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

[22] In fact, the firm size distribution becomes more dispersed due to creative destruction through IT investment. The inclusion of this variable in our regression may bias down the significance of IT variables. However, Section V shows that including this variable does not change the effect of IT at all.

[23] 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

capital investment rate (*I/K*) as the ratio of industry aggregate non-IT investment at time *t* to industry aggregate non-IT capital stock at *t-1* (all in real terms). We use a non-IT investment rate because the total investment rate might be correlated with IT intensity

Other Intangible Assets

Other intangible assets, such as R&D and advertising, might also affect firm-level performance variation, perhaps because they are also modes of investment leading to creative destruction. Both R&D and advertising are highly concentrated in a small number of industries. We also consider book-to-market ratio as a proxy for intangible assets.[24] We discuss R&D and advertising in more detail in Section V and in Appendix II.

Foreign Exposure

A firm's reliance on foreign sales may affect its performance variation. However, to what extent foreign sales affect firm-specific versus systematic (market- and industry-wide) volatility remains as an empirical question. For example, if all the firms in a typical industry trade with a specific country or region, most of the volatility originating abroad would be classified here as systematic. Alternatively, if the firms in a typical industry trade with many different countries, whose economies exhibit low correlations with each other; foreign events would primarily induce firm-specific volatility. 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. Appendix II provides more detail about the

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destruction', systematic volatility (which includes industry-wide volatility) should plausibly be elevated more than firm-specific volatility.

[24] We calculate industry-level book-to-market ratios as the industry aggregate book value of common equity (annual item 60) divided by the industry aggregate market capitalization of common stock (annual

variable.

Firm Diversification[25]

A large literature links corporate diversification with both corporate governance problems and access to capital. In both cases, firm performance volatility could be affected.[26] 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. All else equal, a more leveraged firm experiences more volatile stock returns and accounting earnings. Consequently, industries in which firms are more leveraged might also exhibit greater cross-sectional performance variation. 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) for each industry.

Liquidity might also affect performance variation. The easing of liquidity constraints should increase investment by previously constrained firms, but not other firms. Liquidity is the ratio of current assets (annual item 4) to current liabilities (annual item 5) for each industry.[27]

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item 25 multiplied by annual item 199).

[25] 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 V.

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

II. Construction and Characteristics of the IT Variable

This section outlines the construction of the IT variable. It then examines the variable's characteristics.[28] Appendix I provides technical details.

We obtain industry-level IT data from *Fixed Reproducible Tangible Wealth* (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.[29] 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).[30] We use the Törnqvist index to aggregate these ten types of computer hardware and software into IT capital.[31] Using the same data, we define non-IT capital as all other asset types. Thus, 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 past few decades. The BEA uses a hedonic price method to estimate constant quality prices of computers.[32] The hedonic price falls as the quality of computers rises.[33] For example, memory chip capacity increased at 35 to 45% per year, a

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[27] In robustness checks, we also include controls for institutional ownership, as discussed in Xu and Malkiel (2003) and Dennis and Strickland (2004). These results are not reported in the tables, but including this variable does not qualitatively alter our findings.
[28] In Appendix II, we compare IT and R&D, another possible source of creative destruction, in details.
[29] See Herman (2000) for a detailed description of the data set.
[30] A recent comprehensive revision of the *National Income and Product Accounts* published by the BEA categorizes expenditures on software as fixed investment rather than costs of materials as in COMPUSTAT.
[31] For further details, see Appendix I.
[32] See BEA (1998) for details of the hedonic price method used by the BEA. In general, quality improvement is faster in computers than in software.
[33] Declines in the hedonic price of computers (or equivalently, improvement in the quality of computers) depend on productivity growth associated with technological innovation in IT-producing industries such as

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 real 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 computer 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.

[Insert Table I Here]

Table I shows the cross-industry distribution of IT intensity, the ratio of the IT capital stock to the total capital stock, in 1970, 1980, 1990, and 2000. Variation in IT intensity is substantial across a broad range of industries, and high IT intensity is not a characteristic of only a few high technology industries. On average, IT is more

semiconductor and computer manufacturing industries. For example, Chun and Nadiri (2002) decompose sources of productivity in the U.S. computer industry 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.

intensively used in the non-manufacturing sector than in manufacturing. However, there is a substantial variation of IT intensity within both sectors. Within manufacturing, IT intensity is high in *industrial machinery (including computer-producing firms)*, *electronic equipment (including semiconductor firms)*, *instruments (including laboratory and medical instrument firms)*, *apparels*, and *printing and publishing*. Within the non-manufacturing sector, *wholesale trade* and *business (including software firms)*, *legal*, and *other services industries* exhibit high IT intensity.[34] *Agriculture*, *mining*, *transportation*, and *utilities* all have low IT intensity. Figure 3 illustrates the cross-industry distribution of IT intensity in 2000. 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 V and in Appendix II.

[Insert Figures 3 and 4 Here]

III. Correlation Patterns in Stock Returns, Sales Growth Rates, and ROAs

A. Construction of the Data Series

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

[34] The financial industry is also one of heaviest users of IT within the non-manufacturing sector.

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 (standard deviation) for a given year. Aggregate volatility is the volatility of the value-weighted portfolio consisting of all firms in both CRSP and COMPUSTAT. To gauge micro volatility, we average firm-level volatilities.

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

$$ASales_t = \sum_{i=1}^{N_t} Sales_{i,t} \tag{1}$$

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 2) divided by the price index of relevant industry gross output.[35] 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 $Sales_{i,j,t}$ represents real sales of firm *i* in industry *j* at quarter *t*. In calculating firm-level real 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 using five-year rolling windows.

Aggregate ROA and its volatility are defined similarly.[36] For each quarter *t*, aggregate total assets and aggregate operating income after depreciation are defined as

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

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

where N_t is the number of firms, and $TA_{i,t}$ and $INCOME_{i,t}$ are 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

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

[35] See Appendix I for the construction of the price index of industry gross output.

[36] Total assets are not available on a quarterly basis until 1976. Thus, we calculate micro and macro volatilities of ROA from 1981 on.

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

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

where $INCOME_{i,j,t}$ and $TA_{i,j,t}$ represent the operating income[37] 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.

B. Volatility and Correlation Patterns

As discussed earlier, Figure 1 shows both the aggregate (dotted lines) and firm-level (solid lines) volatilities of stock returns, real sales growth rates, and ROAs. 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 rises steadily over the decades. For example, the difference between firm and aggregate sales growth volatilities is 0.184 for 1971, but grows to 0.346 by 2000. The increased differences are much larger for ROA volatilities, which rise from 0.015 in 1981 to 0.170 in 2000, and stock return volatilities, which rise from 0.043 in 1971 to 0.133 in 2000.[38] When we partition firms into size quintiles, Figure 5 reveals similar patterns in each, with the largest change in the smallest firms. Rising

[37] Operating income after depreciation is not directly 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).

[38] If we use the median of firm-level 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.

firm-level volatility relative to aggregate volatility is evident across the entire corporate sector. This divergence implies declining correlations across firms through the same period.

[Insert Figures 5 and 6 Here]

Figure 6 plots the averages of pairwise correlations of firms' stock returns, real sales growth rates, and ROAs – first for the full sample of firms, then for the firms within the largest quintile, and then for the firms within the smallest quintile. We also calculate the average of pairwise correlations between firms in the largest quintile and firms in the smallest quintile. Average pairwise correlations of stock returns are, on average, higher than those of sales growth and ROA. However, all three exhibit similar declines. Average pairwise correlations within the largest quintile are usually higher than those involving the other groups in the figure, 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 stock return, sales growth, or ROA of firm i in period t, η_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

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

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 volatility or lower common volatility, or both.

IV. Decomposition of Volatility Series

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

To obtain this decomposition, we run regressions as in Durnev *et al.* (2004a):

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

where $r_{i,j,t}$ is stock return, real sales growth rate, or ROA for firm i in industry j at time

t (t represents month for stock return and quarter for real sales growth rate and ROA). $r_{m,t}$ and $r_{j,t}$ are the market index and industry indexes, which are value-weighted averages excluding the firm in question. This exclusion prevents spurious correlations between firm and industry performance measures 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.[39]

Firm-level regression results are aggregated to obtain our industry-level volatility measures. We calculate the *firm-specific volatility* $(\sigma^2_{\varepsilon,j})$ and *systematic volatility* $(\sigma^2_{m,j})$ within industry *j* as:

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

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

where $SSR_{i,j}$ and $SSM_{i,j}$ are the unexplained (squared sum of residual errors) and explained variations of firm *i* in industry *j*. The sums in (11) and (12) are scaled by $\sum_{i\in j} T_i$, the number of firm-month (or firm-quarter) observations available in industry *j*. Thus, the industry-wide average R^2_j can be defined as follows:

[39] Here, we report results based on having at least 15 ROA and real sales growth observations and at least 30 stock return observations. Repeating our tests using alternative restrictions on the number of observations in each regression generates very similar results to those shown in the paper. If we impose no

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

Panels A, B, and C of Figure 7 show the time-series patterns of the equally-weighted and value-weighted averages of each volatility measure. To obtain value-weighted measures, we calculate equally-weighted averages across all firms in an industry and then apply industry weights. For stock return and real sales growth rate, 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).

[Insert Figure 7 and Table II Here]

Several patterns emerge from these figures.

First, firm-specific volatility increases dramatically in stock returns, real sales growth rates, and, to a lesser degree, ROAs. Equally-weighted and industry value-weighted figures look very similar. Increasing firm-specific volatility is not confined to a few large industries. Reflecting this rising firm-specific volatility, the industry-wide average R^2 of (13) also declines over the sample period. For stock returns and real sales growth rates, R^2 falls by about 50% from the mid-1970s to the end of the sample period.

Second, since the mid-1970s, the industry-wide average R^2 of stock returns provides a lower bound for the industry-wide average R^2s of the other two measures. This

restrictions, which basically means we include all new firms, the statistical significance of the results actually improves somewhat.

faster rise in firm-specific volatility relative to systematic volatility for stock returns might reflect additional factors at work in that measure alone – such as increased transparency, as in Huang (2004), Jin and Myers (2004), and Ozoguz (2004), or reduced arbitrage costs, as in Bris *et al.* (2004). However, rising firm-specific volatility is clearly not just confined to stock returns. It is observed in fundamentals (real sales growth and ROA) as well over the whole sample period.

Third, Panel A of Table II shows all three firm-specific volatility measures to be much larger than their corresponding systematic volatility measures. For each year and each industry, we first calculate the ratios of the three firm-specific volatility measures to their analogous systematic volatility measures, and then calculate the means and medians of these three ratios for the whole sample and two sub-periods – 1971-1983 and 1984-2000. The choice of 1984 as the break point reflects the general agreement among economists that the U.S. economy exhibits a structural break at that time.[40] The median ratios reported in the table show that firm-specific volatility for the whole time period is almost five times larger than systematic volatility in stock returns and about three times larger in real sales growth and ROA. The divergence between firm-specific and systematic volatilities becomes more pronounced in the second sub-period in general, especially for stock return and ROA volatilities.

Fourth, in general, firm-specific and systematic volatilities are strongly positively correlated with each other for all three variables (Panel B of Table II). 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

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

inconsistent estimators. However, in this case, the correlation is between two aggregate measures calculated to represent industry-level average firm-specific and 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 volatility, for it suggests that much firm-specific volatility is due to heterogeneous reactions to market-wide shocks. That is, firms often react differently when hit by the same economy-wide shock, thus inducing firm-specific volatility.

Fifth, ROA volatility follows a pattern somewhat different from that of the other two series. The correlation between firm-specific and systematic volatilities is the largest for ROA, and consequently the decrease in its R^2 is the smallest. Part of the high correlations might be due to outliers, for there are several sharp spikes in the comovement of firm-specific and systematic volatility. Dropping both extreme 1% tails of firm-year observations causes the firm-specific 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.[41] Another peculiar characteristic of earnings is that they might be 'managed', while sales and stock return are not. To address this issue, we redo our tests replacing ROAs with cash flow to asset ratios after controlling for accruals using the method of Chan *et al.* (2001). This robustness check generates qualitatively similar results for all the tables in the paper. Further investigation beyond the scope of this study is needed to clarify these issues.

[41] One cause of these outliers is very small total asset numbers.

V. Regression Analyses

In this section, we test whether industries with higher IT intensity exhibit larger firm-specific volatilities. First, we examine the bivariate relationships between our three sets of volatility measures and IT intensity (the ratio of IT capital to total capital). We use IT intensity 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 the three sets of volatility measures in a multiple regression framework controlling for the other industry characteristics described in Section I.B. Since our volatility measures are estimated using five-year windows, we use five-year averages of all the independent variables in our regressions.

A. Bivariate Regressions

We run weighted least square (WLS) regressions for each year and report Fama-MacBeth coefficients and *t*-statistics.[42] 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).[43] We exclude financial industries (1987 SIC codes from 6000 to 6999) because their accounting data (such as sales and ROA) are incompatible with that in other industries. Thus, the maximum

[42] We use WLS to prevent small industries with few firms from being overly influential in our results. However, all our qualitative results do not change even when we use equally-weighted regressions.

[43] As Jin and Myers (2004) note, this may be an overcorrection since spurious serial correlation is possible 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.

number of industries is 50, consisting of 20 manufacturing and 30 non-manufacturing industries.[44] We also discard industries containing fewer than 5 firms, and industries whose IT stock is not defined.

[Insert Table III Here]

Table III presents regressions using IT intensity to explain three sets of volatility measures constructed from stock returns, real sales growth rates, and ROAs, respectively. We apply logarithmic transformations to obtain three *absolute firm-specific volatility* measures, $\ln(\sigma^2_{\varepsilon,j})$, and three *absolute systematic volatility* measures, $\ln(\sigma^2_{m,j})$, for each industry j. Since the R^2 measure is confined within the unit interval and highly skewed, we apply a logistic transformation, as in Durnev *et al*. (2004a), to obtain three *relative firm-specific volatility* measures (ψ_j):

$$\psi_j = \ln(\frac{1-R^2_j}{R^2_j}) = \ln(\sigma^2_{\varepsilon,j}) - \ln(\sigma^2_{m,j}). \tag{14}$$

We report regression results for the whole sample (from 1971 to 2000 for stock returns and real sales growth rates and from 1984 to 2000 for ROAs) and for two sub-periods.[45]

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

[45] The results for ROA are reported for the second sub-period 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 5 firms in an industry to calculate the ROA volatility series, and this condition is met in only thirty industries through the early 1980s. Thus we perform regressions from the mid-1980s for ROA.

[Insert Figure 8 Here]

Our central finding is that absolute firm-specific volatility in stock returns, sales growth rates, and ROAs is strongly positively correlated with IT intensity. Figure 8 (Panels A, B, and C) graphs the relationship between IT intensity and absolute firm-specific volatility in 2000.[46] IT intensity is also positively correlated with absolute systematic volatility.

Relative firm-specific volatility (ψ) captures the importance of absolute firm-specific volatility relative to absolute systematic volatility. Table III shows that IT intensity is positively significantly (p-value < 1%) related to relative firm-specific stock return volatility for the full sample period. IT intensity is also positively related to relative firm-specific sales growth volatility, but this is only significant at 10%. IT intensity becomes more strongly correlated with relative firm-specific sales growth volatility in the post-1984 sub-period, when the significance level improves to below 1%.

The results for volatility measures based on ROAs are weaker than those for volatility measures based on sales growth rates or stock returns. Even though IT intensity explains absolute firm-specific ROA volatility, it fails to explain relative firm-specific ROA volatility – and even has the wrong (negative) sign.

The bivariate regressions involving absolute firm-specific stock returns volatility in Table III have substantial adjusted R^2s – over 40% for the whole sample. The adjusted R^2s for the regressions using absolute systematic and relative firm-specific returns

[46] In Figure 8, industries with both high firm-specific volatility and high IT intensity include manufacturing industries such as *industrial machinery* and *instruments* and non-manufacturing industries such as *business services* and *wholesale trade*. This illustrates how the relationship between IT and firm-specific volatility is economy-wide, not just confined to a specific group of industries such as dotcoms.

volatility are also substantial. The R^2s for the regressions using absolute firm-specific sales growth and ROA volatilities are also respectable, though lower. The regressions using relative firm-specific volatilities in sales growth rates and ROAs have significantly lower adjusted R^2s, however.

A weaker relationship with sales growth and ROA volatilities than with stock returns volatilities might be attributed to data quality. The volatilities of sales growth and ROA must be estimated using quarterly observations. Our stock returns volatility measures, however, can be estimated using monthly data, and so are more precisely estimated.

In the following section, we move on to multiple regressions to control for the effect of other industry characteristics that could affect our volatility measures. Multiple regression analyses can also address possible omitted variables bias in our bivariate regressions.

B. Multiple Regressions

In this section, we include all the industry-level control variables, described in Section I.B, in our regressions. These controls consist of average firm age, non-IT capital investment, a Herfindahl-Hirschman Index, leverage, liquidity, a firm size distribution measure, foreign exposure, firm diversification, and measures of intangibles such as research and development (R&D), advertising, and book-to-market ratio.[47]

[Insert Table IV Here]

Table IV reports the averages of annual cross-sectional correlation coefficients between all pairs of the variables of interest in our multiple regressions, as well as their associated significance levels. Note that IT intensity is strongly positively correlated with R&D and advertising intensities. 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 has been used in many studies as a 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. 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.

[Insert Tables V and VI Here]

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

The key results from Tables V and VI are as follows.

First, IT is significantly positively correlated with both absolute and relative firm-

[47] See Section I.B and Appendix I for details about the construction of each variable.

specific volatilities.[48] These findings are consistent with IT being related to the process of creative destruction because creative destruction increases heterogeneity among firms, which is captured by increases in both absolute firm-specific and relative firm-specific volatilities. In fact, IT is the only variable that explains both volatility measures with a consistently significantly positive sign throughout the sample period.

Second, despite the patterns evident in the graphs and bivariate regressions discussed above, IT intensity turns out not to be significantly related to absolute systematic volatility when we include the controls, especially R&D intensity.[49] The component of IT related to absolute systematic volatility is highly correlated with R&D intensity, and this explains the significant relationship between IT and absolute systematic volatility in bivariate regressions. Also, IT attracts a positive and significant coefficient in regressions explaining relative firm-specific stock returns and sales growth volatilities; but R&D does not. Overall, IT seems related to firm-specific 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, many of which are quite sensitive to the particular specification. For example, when only IT intensity, firm age, *I/K* (non-IT investment over non-IT capital stock), and book-to-market ratio are included, book-to-market is negatively related to both the absolute firm-specific and absolute systematic

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[48] Out of 21 bivariate regression results reported in the Table III, there is only one case (relative firm-specific volatility of ROA) in which IT intensity attracts a negative and significant (p-value < 5%) coefficient. In the multiple regressions, this negative relationship disappears.

[49] As noted above, R&D is quite concentrated in a few industries 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 and R&D intensities. R&D intensity remains significant, suggesting its coefficient is not a mere artefact of business cycle exposure.

volatility measures. However, when we include more controls, the sign becomes positive for the absolute volatility measures. This instability and the multiple interpretations possible for some controls make interpreting their coefficients and significance levels problematic. Thus, in the following discussion, we focus on variables that show relatively identifiable patterns.

Except for the IT intensity, the Herfindahl-Hirschman index (*HHI*) and advertising are the only two variables that attract positive and significant coefficients for relative firm-specific volatilities (4 and 5 respectively out of 7 cases shown in Table V.) However, their relationships with absolute firm-specific volatilities are not uniform. For example, the coefficients of *HHI* in regressions explaining absolute firm-specific volatilities are either negative and significant, as in two cases for the first sub-sample, or positive and significant, as in one case for the second sub-sample. This unstable pattern is consistent with absolute firm-specific volatilities being insignificant in the whole sample. Advertising generally attracts insignificant coefficients in regressions explaining absolute firm-specific volatilities. The two exceptions are in regressions of absolute firm-specific sales growth rate volatility in the second sub-sample, where its coefficient is positive and significant; and absolute firm-specific ROA volatility, where its coefficient is negative and significant. This instability makes interpreting the coefficient problematic.

Firm age is typically negatively related to both absolute firm-specific and systematic volatility measures, but its explanatory power for relative firm-specific volatility is slight. The coefficients of the firm size distribution measure suggest that industries in which all firms are nearly the same size have lower volatility – both firm-specific and systematic.

Including firm diversification and foreign exposure in the Table VI regressions barely changes the signs and significance of IT intensity in explaining all the volatility measures.

C. 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. Fifth, we repeat our analysis including institutional ownership as an additional control. This cuts down our sample period, as the ownership data are not readily available for all the years we study. None of these alternative approaches qualitatively changes our results.

D. Endogeneity

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

The converse, that high firm-specific volatility causes IT intensity, might follow if more volatile industries invest more in IT capital to decrease 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 firm-specific 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 use the following regression:

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

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

[50] We also tried different horizons (from one to ten years) to measure volatility growth rates. Qualitative results of the paper do not change.

residuals, $\varepsilon_{j,t+1}$, may contain a common factor that affects 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 firm-specific volatility because, by construction, that measure is independent of common shocks. There can thus be no such relationship between the residuals and $Vol_{j,t}$. However, specifications using absolute systematic volatility or relative firm-specific volatility could be vulnerable to this problem. Consequently, caution is warranted in interpreting results for these two volatility measures.

[Insert Table VII Here]

Table VII 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 firm-specific volatility rises *following* periods of high IT intensity.[51] The sole exception is absolute firm-specific stock return volatility using the whole sample, where β is still positive, but the *t*-statistic is only 1.67 and in the early sub-sample, where β becomes utterly insignificant. Relative firm-specific volatility also rises subsequent to high IT intensity, most markedly in the second sub-period. Relative firm-specific volatility in ROA is insignificant in the second sub-period, mirroring our earlier cross-

[51] Despite the small coefficient on the IT variable compared to that of the lagged volatility variable, the former is statistically important in explaining cross-industry variation in volatility growth. For example, in regressions of the stock return volatility measures for the whole sample, adding the IT variable raises adjusted R^2 from 0.147 to 0.215 for absolute firm-specific volatility and from 0.125 to 0.376 for relative firm-specific volatility.

sectional bivariate regression results. Note also that γ is negative. Thus the intensity of creative destruction (measured by firm-specific volatility) tends to decrease over time, all else equal, in the absence of sustained IT investment.

Results in Table VII are 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.

VI. Conclusion

We find that higher firm-specific volatility in individual firms' stock returns, real sales growth rates, and ROAs is associated with higher investment in IT. These findings are robust to a wide range of specification changes and to the inclusion of control variables: average firm age, non-IT capital investment, a Herfindahl-Hirschman Index, leverage, liquidity, a firm size distribution measure, foreign exposure, firm diversification, and measures of intangibles such as research and development, advertising, and book-to-market ratio. Volatility rises subsequent to periods of high 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 intensified the pace of 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 volatilities in the economy aggregate stock market return, sales growth rate, and ROA fell while volatilities in individual firms' stock returns, sales growth rates, and ROAs all rose. The firm-specific volatilities of all these performance measures rose faster than their systematic counterparts, thus decreasing their correlations 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.* (2004a), Huang (2004), Jin and Myers (2004), and Ozoguz (2004) present evidence consistent with interpreting firm-specific volatility 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) volatility measures based on stock returns and fundamentals are unrelated to IT intensity after controlling for the effect of R&D intensity. The component of IT intensity related to systematic volatility 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).[52] 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 (δ_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 in each industry, 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

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

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

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

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

Finally, the ratio of aggregate real capital stock is

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

R&D and Advertising

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

$$RD_t = \sum_{k=0}^{4} (1 - k\delta) RDE_{t-k} \tag{A.5}$$

where RD is R&D capital stock, RDE is R&D expenditures, and δ is a 20% straight-line depreciation rate.[53] To construct comparable intensities for IT and R&D, we define R&D intensity as the ratio of real R&D capital stock to real PPE (property, plant, and equipment, annual item 8). PPE in COMPUSTAT is the closest definition to total capital in *Fixed Reproducible Tangible Wealth* (FRTW) as published by the BEA. 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 methods. 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.

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

[53] 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

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.

Appendix II: IT versus 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 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.

First, in contrast to IT investment, R&D spending is highly concentrated in a few industries (see Figures 3 and 4.), and in a few large firms in those industries to boot. Figure 4 shows the cross-industry distribution of R&D intensity (the ratio of R&D capital to PPE) in 2000. R&D intensity is exceptionally high in five durable goods manufacturing industries (from *industrial machinery* to *miscellaneous manufacturing*), *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

average, 25%.

accounted for almost 80% of total R&D spending in the manufacturing sector (NSF, 2003).[54]

In contrast, more than 75% of industries have R&D intensity below one percent. And in a sizeable fraction of industries, most firms report no R&D activity whatsoever. 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 that over 70% of R&D spending is 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. It is a general purpose technology, whose application creates value proportional to certain complementary inputs, such as managerial talent and allows qualitative product

[54] 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 services* firm because its sales of software and computer related services are greater than its sales of computer hardware.

differentiation in a broad cross-section of industries. Thus R&D and IT investments may, at the present time in the U.S. economy, typically represent two qualitatively different forms of innovation.

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.

This 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 the probabilities of each winning the race remain constant. This leads to industry-wide comovement. Once it becomes clearer which firms are winning, their prices begin to diverge from those of the losers. This results in firm-specific volatility.[55] 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.

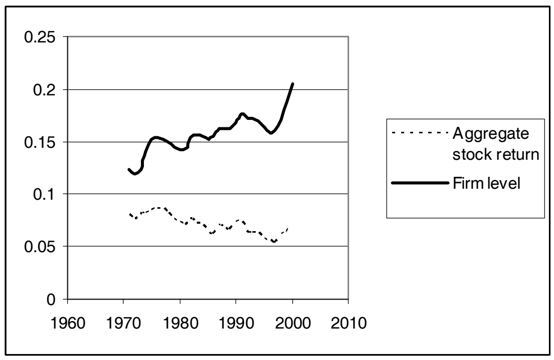
Berk *et al.* (2004), citing the same prolonged R&D investment period, propose another mechanism through which R&D activity might correlate with systematic volatility. They point out that, unlike major capital investments, which are undertaken in a given year and then become sunk costs, investment in 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 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 V shows that R&D intensity is related to systematic volatility 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.

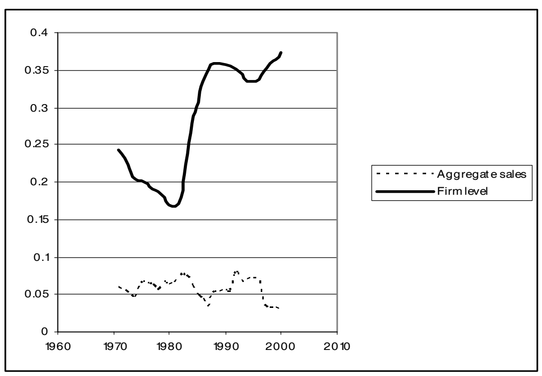
[55] This line of reasoning follows from Shiller (1989).

Figure 1. Aggregate (Macro) and Firm-Level (Micro) Volatilities, 1971-2000
This figure plots aggregate and firm-level volatilities of monthly stock returns, quarterly real sales growth rates, and quarterly returns on asset (ROA). Aggregate stock return volatility is calculated using the value-weighted portfolio consisting of all firms both in CRSP and COMPUSTAT using five-year rolling windows. 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 five-year rolling windows. Firm-level volatilities are averages of the volatilities of stock returns, real sales growth rates, and ROAs of all firms in the sample. The sample period is 1971-2000 for stock returns and real sales growth rates, and 1981-2000 for ROAs.

(a) Stock return



(b) Real sales growth rate



(c) ROA

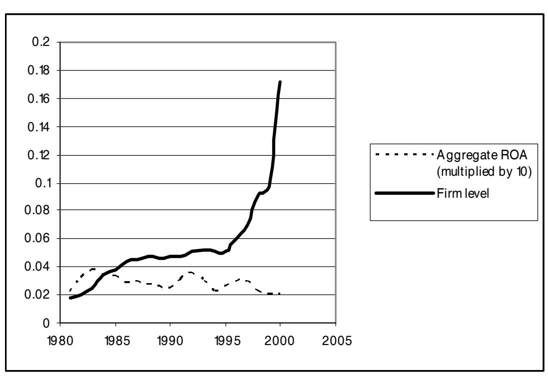
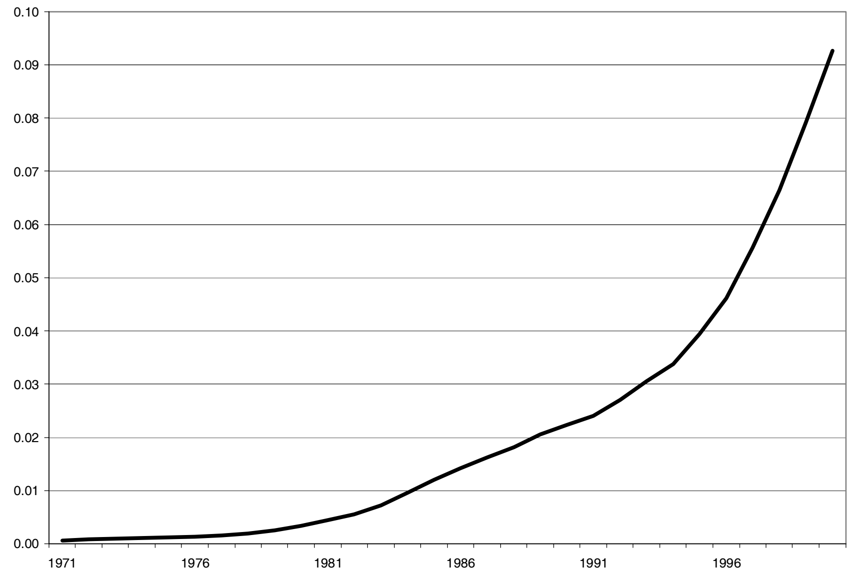


Figure 2. Time-Series and Cross-Sectional Patterns of IT Intensity, 1971-2000

Figure 2(a) plots aggregate IT intensity in 1994 real dollars. Aggregate IT intensity is the ratio of aggregate IT capital to aggregate total capital (the sum of IT and non-IT capital). IT capital is the sum of computers and software. Both IT and non-IT capital are obtained from *Fixed Reproducible Tangible Wealth* (FRTW), published by the *Bureau of Economic Analysis* (BEA). Figure 2(b) illustrates the cross-industry distribution of the logarithm of IT intensity in 1994 real dollars.

(a) Time-series pattern of aggregate IT intensity



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

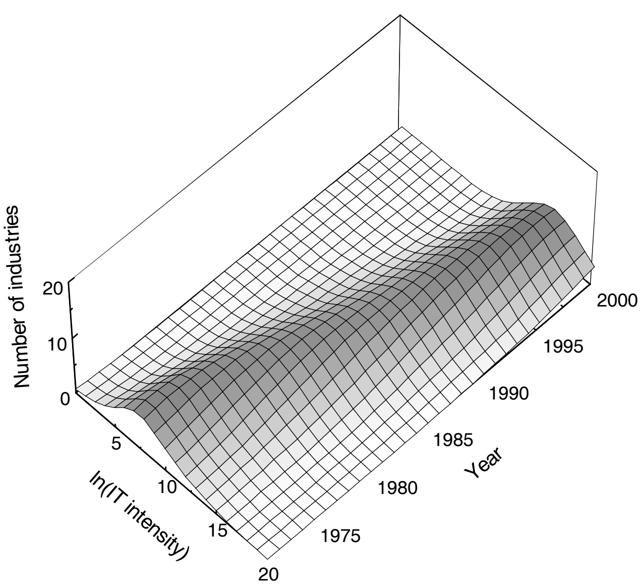


Figure 3. Cross-Industry Distribution of IT Intensity in U.S. Industries, 2000

IT intensity is defined as the ratio of IT capital to total capital (the sum of IT and non-IT capital), all in 1994 real dollars. IT capital is defined as the sum of computers and software.

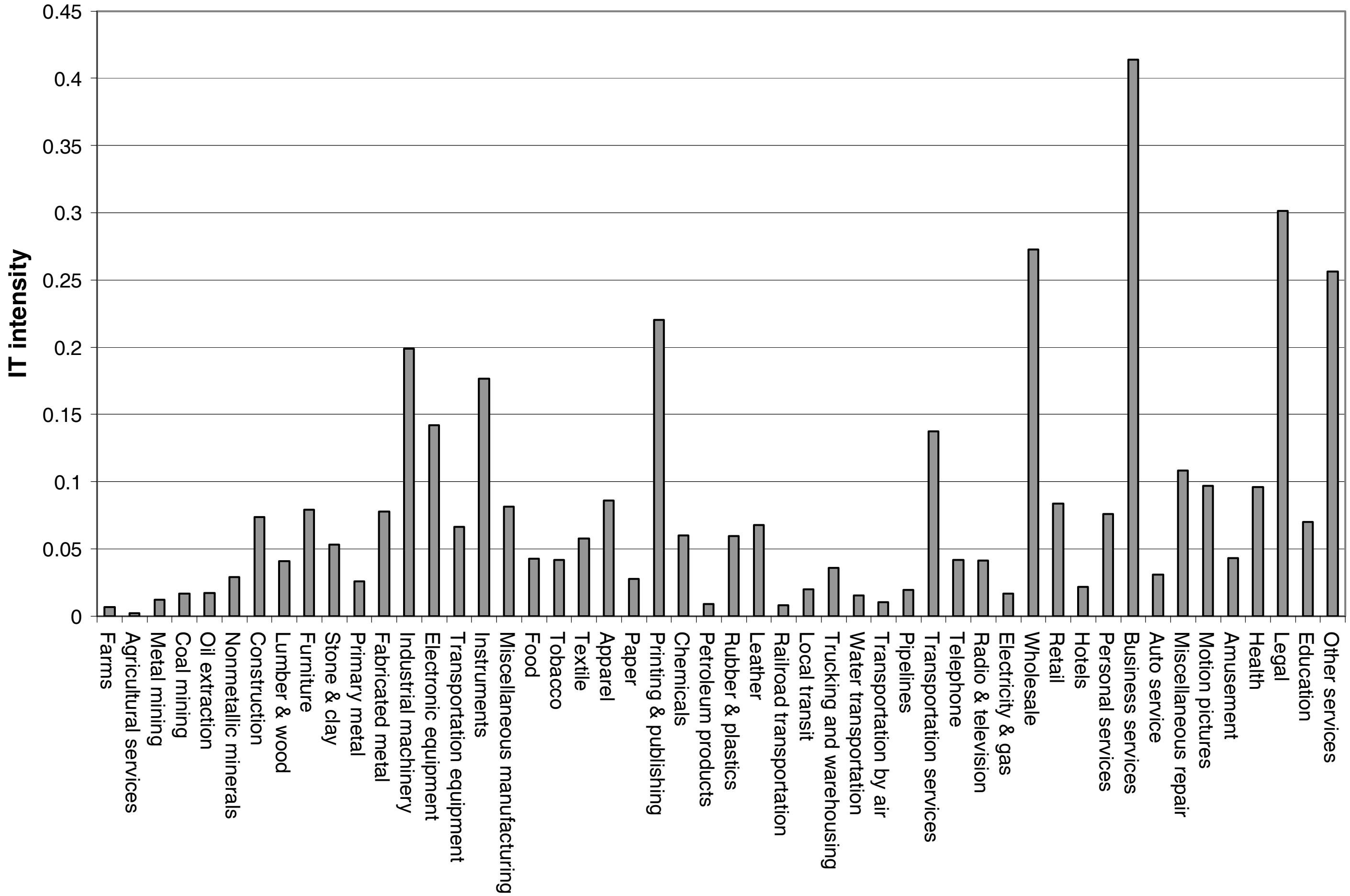


Figure 4. Cross-Industry Distribution of R&D Intensity in U.S. Industries, 2000
R&D intensity is the ratio of R&D capital to property, plant, and equipment (PPE), all in 1994 dollars. For comparison with IT intensity (the ratio of IT capital to total capital), R&D capital is scaled by PPE from COMPUSTAT, which is the closest analog to total capital in FRTW.

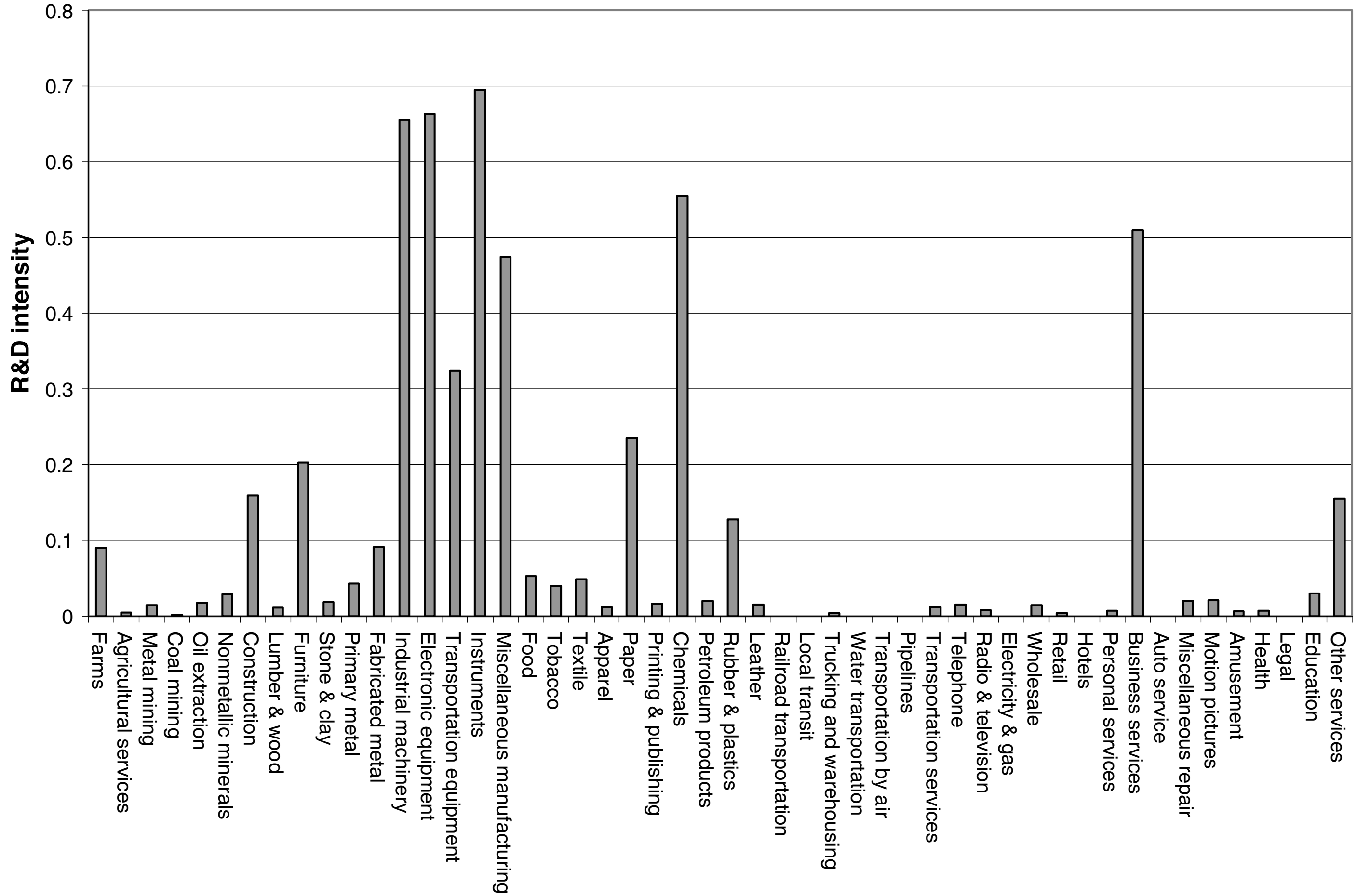
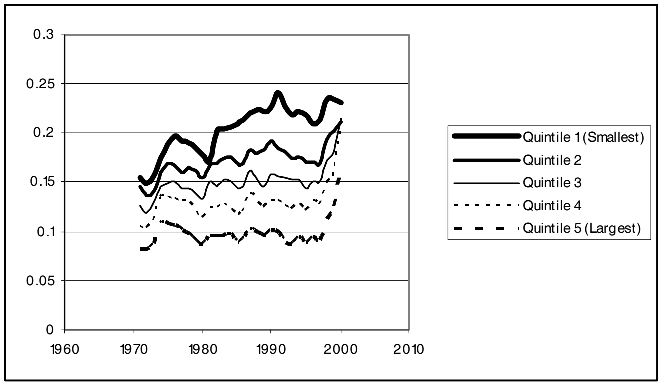
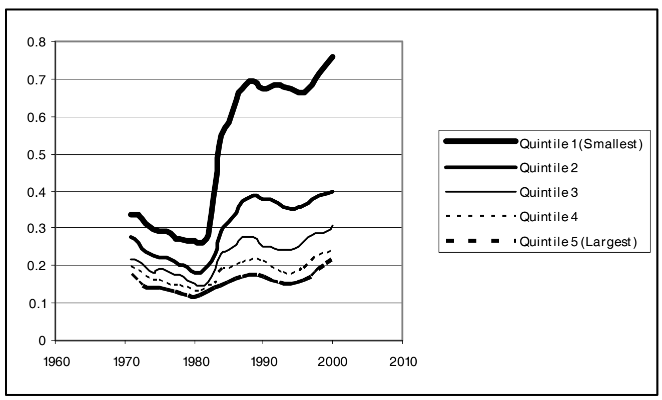


Figure 5. Firm-Level Volatility by Size Quintiles
This figure plots equally-weighted average of firm-level volatilities for each size quintile.

(a) Stock return



(b) Real sales growth rate



(c) ROA

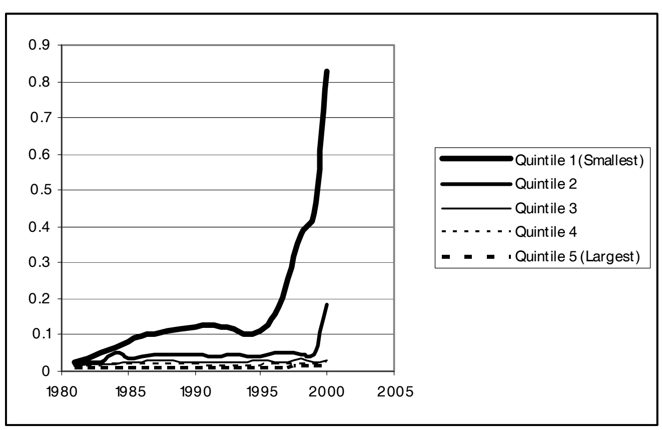
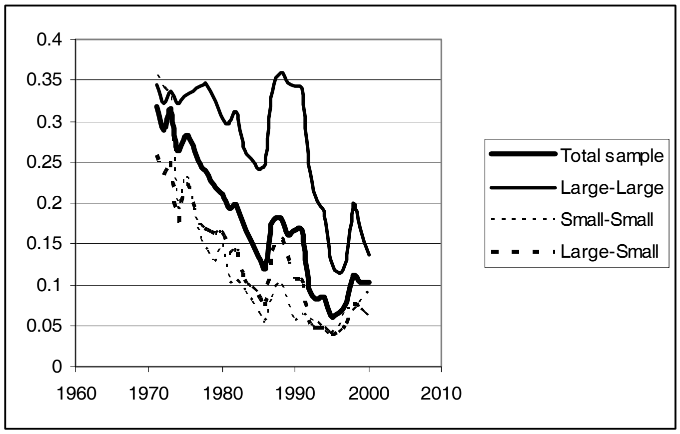
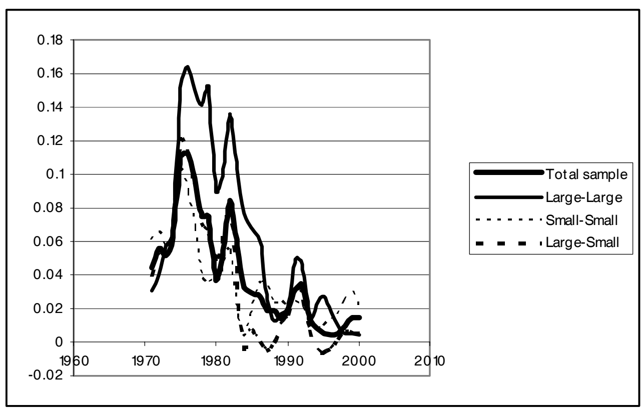


Figure 6. Patterns of Average Correlations
This figure plots the averages of firm-level pairwise correlation coefficients of stock return, real sales growth rate, and ROA. Large-Large (Small-Small) indicates the average pairwise correlation patterns among the firms in the 5th quintile (1st quintile). Large-Small denotes the average pairwise correlation patterns between firms in the 5th quintile and firms in the 1st quintile.

(a) Stock return



(b) Real sales growth rate



(c) ROA

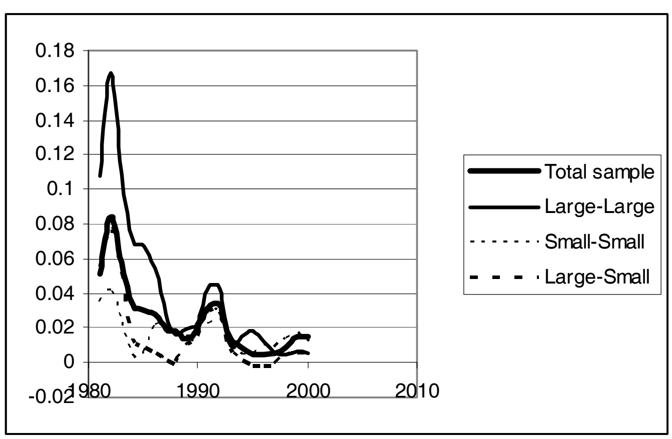
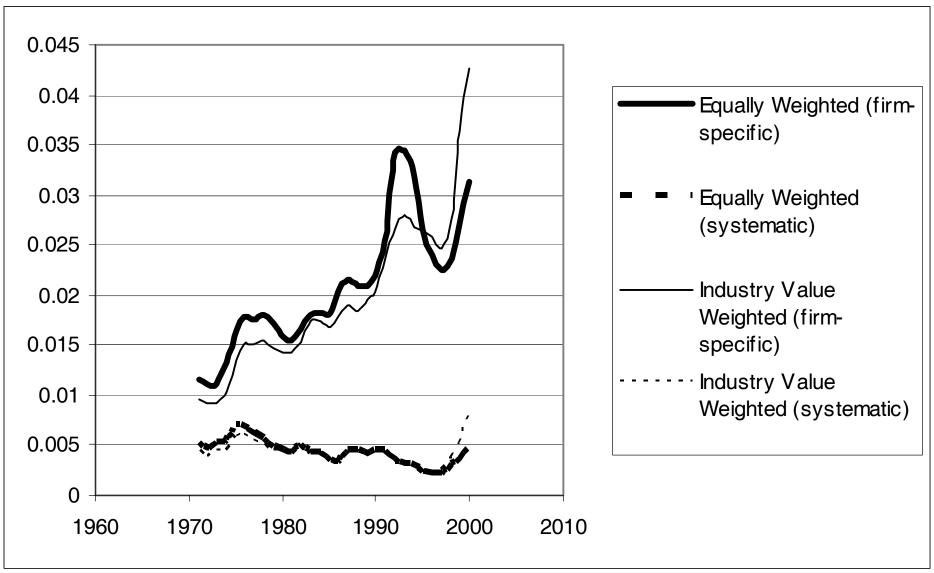


Figure 7. Volatility Decompositions

This figure plots the equally-weighted and value-weighted (using 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 industry weight to obtain value-weighted averages. Systematic volatility (σ_m^2) is firm-level volatility related to market-wide and industry-wide events. Firm-specific volatility is firm-level volatility related to other events. Total volatility is the sum of systematic volatility and firm-specific volatility $(\sigma_m^2 + \sigma_\varepsilon^2)$. Systematic as a faction of total volatility (R^2) is also reported.

Panel A: Equally- and value-weighted volatility measures based on stock returns

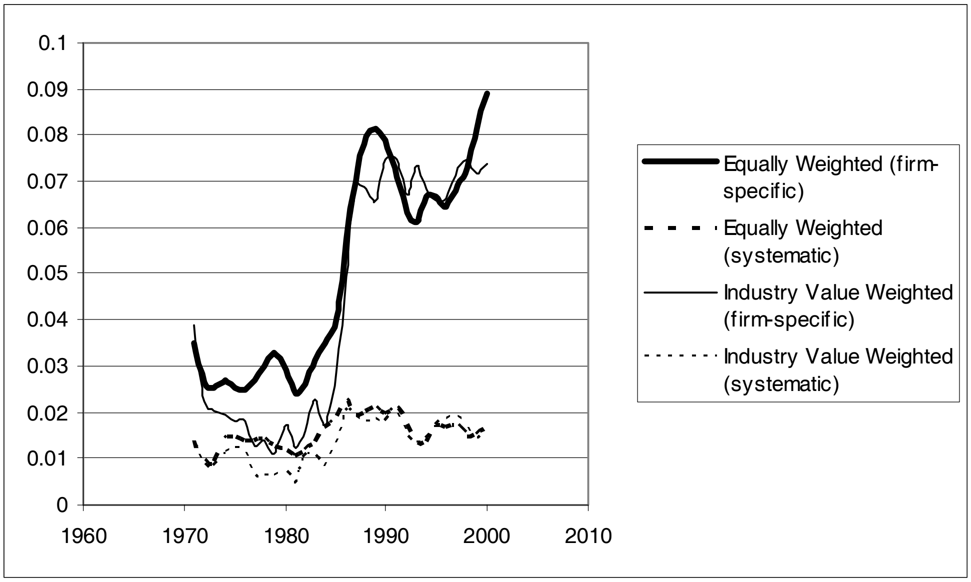
(i) Firm-specific and systematic volatilities in stock returns



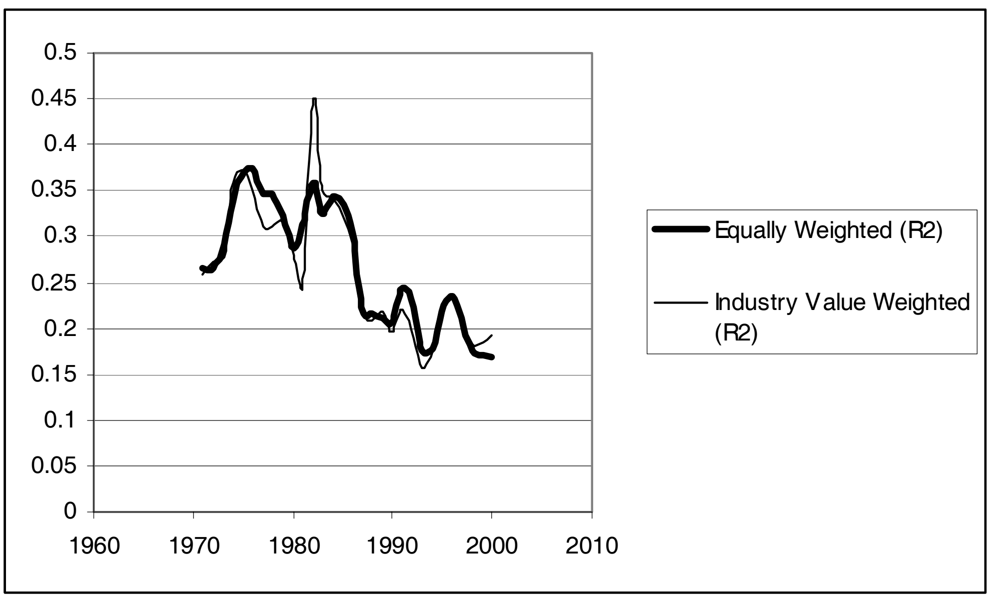
(ii) Systematic as a fraction of total volatility (R^2) in stock returns

Panel B: Equally- and value-weighted volatility measures based on real sales growth rates

(i) Firm-specific and systematic volatilities in real sales growth rates

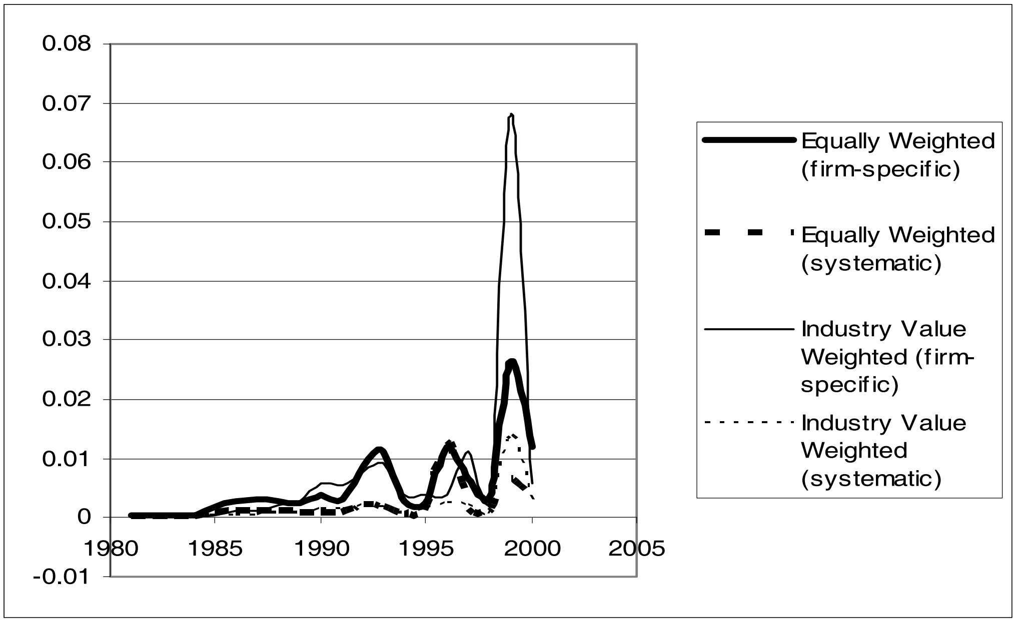


(ii) Systematic as a fraction of total volatility (R^2)in real sales growth rates



Panel C: Equally- and value-weighted volatility measures based on ROAs

(i) Firm-specific and systematic volatilities in ROAs



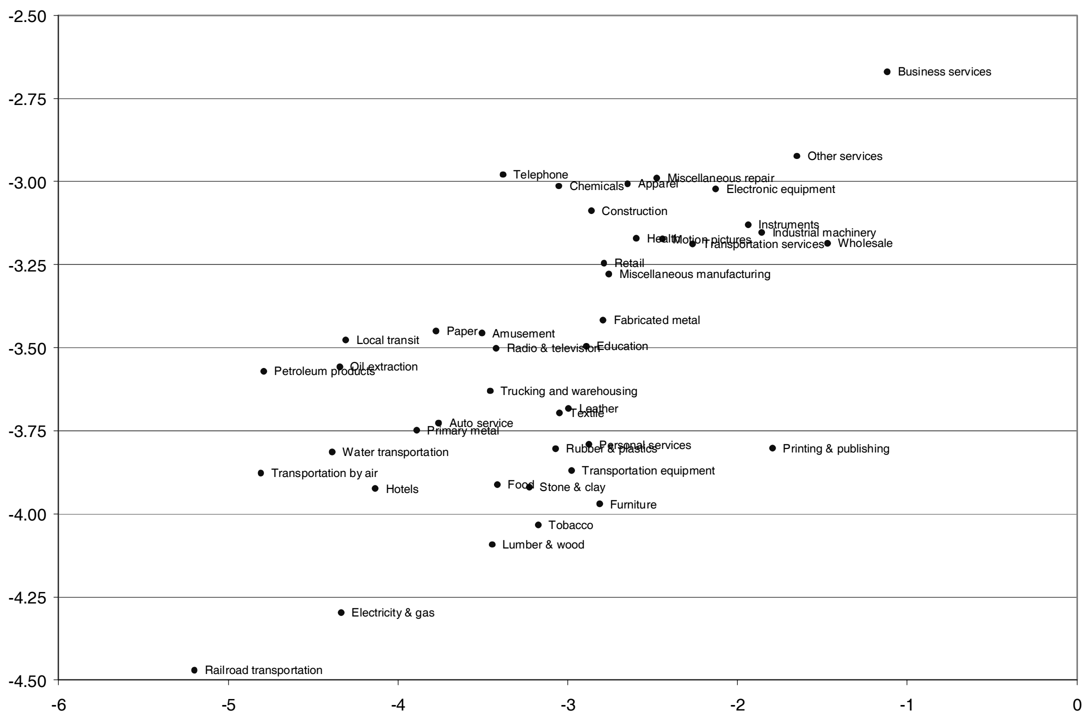
(ii) Systematic as a fraction of total volatility (R^2)in ROAs

Figure 8. IT Intensity and Absolute Firm-Specific Volatility in 2000

These graphs plot the logarithm of IT intensity against our absolute firm-specific volatility measures in 2000. Bivariate WLS regression results for 2000 are also reported. All regressions are weighted by industry shares of market capitalization, sales, and total assets for stock return, real sales growth, and ROA regressions, respectively. Dependent variables are absolute firm-specific volatilities $(\ln(\sigma_\varepsilon^2))$ for stock returns, real sales growth rates, and ROAs. IT intensity (*IT*) is the ratio of IT capital to total capital (all in 1994 real dollars). IT capital is the sum of computers and software. Since our volatility measures are constructed using five-year rolling windows, we use a five-year average IT intensity. In constructing volatility measures, firms with fewer than 30 monthly stock return observations and firms with fewer than 15 quarterly real sales growth or ROA observations for are dropped. The sample also excludes industries with fewer than five firms and whose IT capital is undefined. Finance industries (SIC code 6000-6999) are omitted. *t*-statistics are calculated from heteroskedasticity-consistent standard errors.

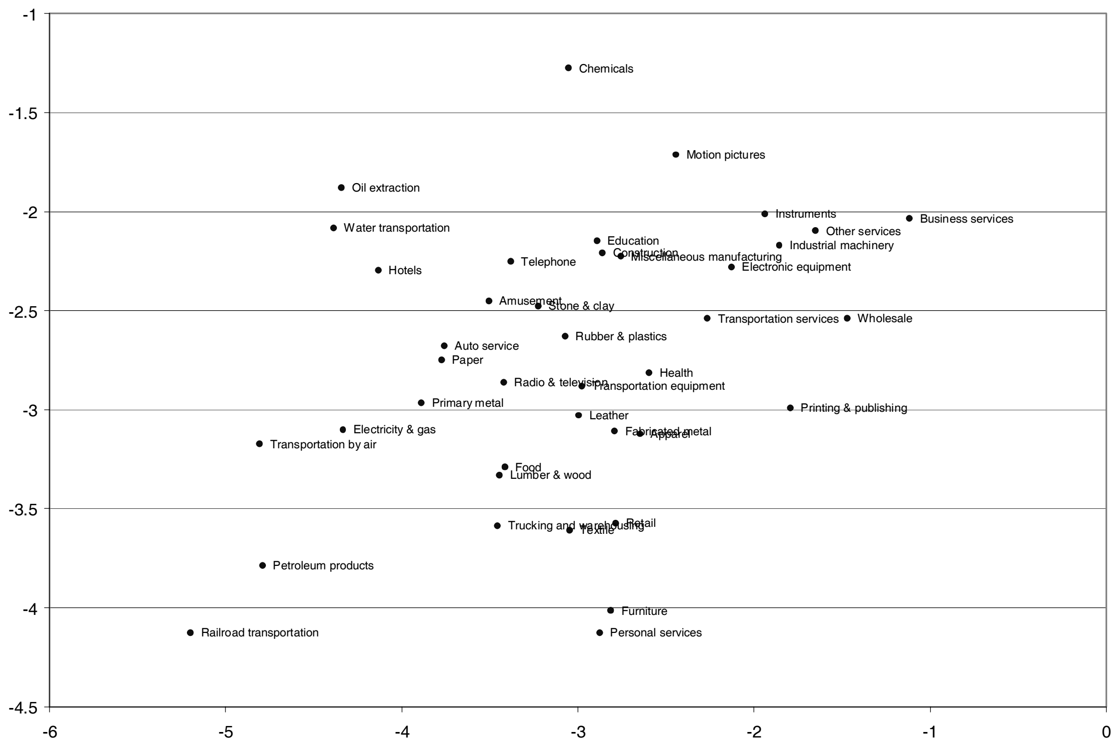
Panel A: IT intensity and absolute firm-specific volatility of stock return in 2000

$$\ln({}_{Stock}\sigma_\varepsilon^2) = -2.472 + 0.273\ ln(IT) \qquad adjusted\ R^2 = 0.390$$
$$(t\text{-}stat=4.003) \qquad sample\ size = 43$$



Panel B: IT intensity and absolute firm-specific volatility of real sales growth in 2000

$$\ln({}_{Sales}\sigma_{\varepsilon}^{2}) = -1.719 + 0.340\ ln(IT) \qquad adjusted\ R^2 = 0.230$$
$$(t\text{-}stat=3.243) \qquad sample\ size= 40$$



Panel C: IT intensity and absolute firm-specific volatility of ROA in 2000

$$\ln({}_{ROA}\sigma_{\varepsilon}^{2}) = -2.668 + 1.168\ ln(IT) \quad adjusted\ R^2 = 0.559$$
$$(t\text{-}stat=6.698) \quad sample\ size= 40$$

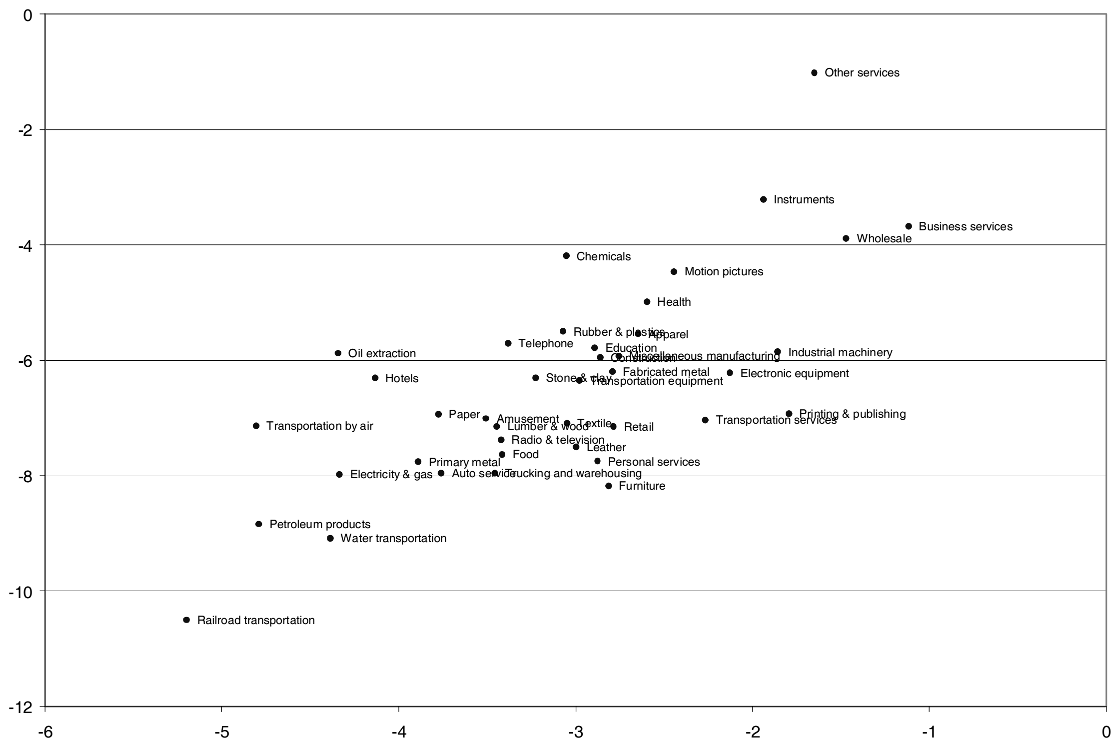


Table I
IT Intensity by Industry and by Year: 50 Industries and 1970, 1980, 1990, and 2000

IT intensity is the ratio of IT capital to total capital (the sum of IT and non-IT capital stock) in percentage. IT capital is defined as the sum of computers and software. Finance industries (SIC code 6000-6999) are omitted.

		IT Intensity in Nominal Dollars				IT Intensity in 1994 Real Dollars			
Sector	Industry	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 I
IT Intensity by Industry and by Year: 50 Industries and 1970, 1980, 1990, and 2000
[Continued]

		IT Intensity in Nominal Dollars				IT Intensity in 1994 Real Dollars			
Sector	Industry	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 II
Time-Series Patterns of Decomposed Volatility Measures

In panel A, we first calculate the ratio of firm-specific volatility over 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 firm-specific volatility and systematic volatility for each industry and then calculate averages and medians for the whole sample and for each sub-period. Systematic volatility is firm-level volatility related to market-wide or industry-wide events.

Panel A: The ratio of firm-specific volatility to systematic volatility

		Stock Return	Sales Growth	ROA
Whole	Mean	6.044	4.857	7.101
(1971-2000)	Median	4.584	3.159	3.273
	N	1431	1388	920
First Period	Mean	3.290	3.060	3.952
(1971-1983)	Median	2.937	2.227	2.471
(1981-1983 for ROA)	N	609	566	128
Second Period	Mean	8.084	6.095	7.610
(1984-2000)	Median	6.626	3.895	3.380
	N	822	822	792

Panel B: Correlations between firm-specific and systematic volatilities

		Stock Return	Sales Growth	ROA
Whole	Mean	-0.033	0.558	0.712
(1971-2000)	Median	-0.021	0.612	0.836
	N	49	49	49
First Period	Mean	0.320	0.417	0.295
(1971-1983)	Median	0.348	0.454	0.689
(1981-1983 for ROA)	N	48	45	42
Second Period	Mean	0.181	0.480	0.703
(1984-2000)	Median	0.218	0.536	0.814
	N	49	49	49

Table III
Fama-MacBeth Cross-Sectional Bivariate Regressions of Volatilities on IT

Regressions are estimated with WLS over a cross-section of industries for each year. Observations are weighted by industry shares of market capitalization, sales, and total assets for regressions explaining volatility measures based on stock returns, real sales growth rates, and ROAs, respectively. Dependent variables are absolute firm-specific $(\ln(\sigma_\varepsilon^2))$, absolute systematic $(\ln(\sigma_m^2))$, and relative firm-specific $(\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2))$ volatilities for stock returns, real sales growth rates, and ROAs. Systematic volatility is firm-level volatility related to market-wide and industry-wide events. The sample period is 1971-2000 for stock return and real sales growth and 1984-2000 for ROA. IT intensity (*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. Since our volatility measures are constructed using five-year rolling windows, we use the five-year average of IT intensity. In constructing volatility measures, firms with fewer than 30 monthly stock return observations or fewer than 15 quarterly real sales growth or ROA observations are excluded. The sample also excludes industries with fewer than 5 firms and industries whose IT capital is not defined. Finance industries (SIC code 6000-6999) are omitted. Average coefficients are calculated as in Fama-MacBeth, but *t*-statistics are adjusted for autocorrelation and heteroskedasticity using the method of Newey and West (1987) as modified in Pontiff (1996). Intercept estimates are not reported. 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. firm.	0.409	40.733	**0.259**[a]	12.891
	Stock	abs. syst.	0.215	40.733	**0.156**[a]	7.200
	Stock	rel. firm.	0.246	40.733	**0.102**[a]	7.249
	Sales	abs. firm.	0.213	36.500	**0.274**[a]	12.107
	Sales	abs. syst.	0.133	36.500	**0.233**[a]	6.560
	Sales	rel. firm.	0.030	36.500	**0.040**[c]	1.792
1971-1983	Stock	abs. firm.	0.477	39.769	**0.268**[a]	16.707
	Stock	abs. syst.	0.238	39.769	**0.142**[a]	12.668
	Stock	rel. firm.	0.340	39.769	**0.126**[a]	16.614
	Sales	abs. firm.	0.226	32.538	**0.280**[a]	24.633
	Sales	abs. syst.	0.183	32.538	**0.295**[a]	13.297
	Sales	rel. firm.	-0.009	32.538	-0.015	-0.766
1984-2000	Stock	abs. firm.	0.357	41.471	**0.251**[a]	8.156
	Stock	abs. syst.	0.197	41.471	**0.167**[a]	4.801
	Stock	rel. firm.	0.175	41.471	**0.084**[a]	4.060
	Sales	abs. firm.	0.204	39.529	**0.269**[a]	6.957
	Sales	abs. syst.	0.094	39.529	**0.186**[a]	4.052
	Sales	rel. firm.	0.060	39.529	**0.083**[a]	7.856
	ROA	abs. firm.	0.319	36.647	**0.751**[a]	7.652
	ROA	abs. syst.	0.336	36.647	**0.852**[a]	13.490
	ROA	rel. firm.	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 IV
Average Cross-Sectional Correlation Coefficients between Control Variables

Average cross-sectional correlation coefficients between control variables are calculated for 1971-2000. IT intensity (*IT*) is the ratio of IT capital to total capital (all in 1994 real dollars). *AGE* is the average age of firms in an industry based on the listing year in CRSP. *I/K* is the ratio of non-IT investment in year *t* to non-IT capital in year *t-1*. Book-to-market (*BM*) is the ratio of common equity to market capitalization of common stock. *RD* and *ADV* are the ratios of R&D capital stock and advertising expenditure to property, plant, and equipment (PPE), respectively (all in 1994 real dollars). Herfindahl-Hirschman Index (*HHI*) is calculated using sales. Dispersion (*DIS*) is the standard deviation of the logarithm of firm size (market capitalization) for each industry. 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. Foreign exposure (*FE*) is the ratio of foreign sales to the sum of domestic and foreign sales. Firm diversification (*SEG*) is the average number of two-digit segments. Correlation coefficients with either foreign exposure or diversification are reported for 1989-1997. Since our volatility measures are constructed using five-year rolling windows, we use five-year averages of all control variables. Finance industries (SIC code 6000-6999) are omitted. Numbers in parentheses are *p*-values. Coefficients significant at 10% or better are in boldface.

	ln(IT)	*ln(AGE)*	*I/K*	*BM*	*ln(1+RD)*	*ln(1+ADV)*	*HHI*	*DIS*	*LEV*	*LIQ*	*FE*
ln(AGE)	-0.170										
	(0.247)										
I/K	**0.331**	**-0.273**									
	(0.014)	**(0.048)**									
BM	**-0.290**	**0.250**	**-0.346**								
	(0.039)	**(0.073)**	**(0.009)**								
ln(1+RD)	**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)					
DIS	-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)				
LEV	-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)			
LIQ	**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)**		
FE	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)	
SEG	**-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 V
Fama-MacBeth Cross-Sectional Multivariate Regressions of Volatilities on IT

Regressions are estimated with WLS over a cross-section of industries for each year. Observations are weighted by industry shares of market capitalization, sales, and total assets for regressions explaining volatility measures based on stock returns, real sales growth rates, and ROAs, respectively. Dependent variables are absolute firm-specific $(\ln(\sigma_{\varepsilon}^2))$, absolute systematic $(\ln(\sigma_m^2))$, and relative firm-specific $(\ln(\sigma_{\varepsilon}^2)-\ln(\sigma_m^2))$ volatilities for stock returns, real sales growth rates, and ROAs. Systematic volatility is firm-level volatility related to market-wide and industry-wide events. In constructing volatility measures, we use five-year rolling windows, and drop firms with fewer than 30 monthly stock return observations or fewer than 15 quarterly sales growth or ROA observations. We further drop industries with fewer than 5 firms or whose IT capital is undefined. Finance industries (SIC code 6000-6999) are omitted. IT intensity (*IT*) is the ratio of IT capital to total capital (all in 1994 real dollars). *AGE* is the average age of firms in an industry based on the listing year in CRSP. *I/K* is the ratio of non-IT investment in year *t* to non-IT capital in year *t-1*. Book-to-market (*BM*) is the ratio of common equity to market capitalization of common stock. *RD* and *ADV* are the ratios of R&D capital stock and advertising expenditure to property, plant, and equipment (PPE), respectively (all in 1994 real dollars). Herfindahl-Hirschman Index (*HHI*) is calculated using sales. Dispersion (*DIS*) is the standard deviation of the logarithm 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 the ratio of current assets to current liabilities. Since our volatility measures are constructed using five-year rolling windows, we use five-year averages of all control variables. Average coefficients are calculated as in Fama-MacBeth, but *t*-statistics are adjusted for autocorrelation and heteroskedasticity using the method of Newey and West (1987) as modified in Pontiff (1996). Intercept estimates are not reported. 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+ RD)*	*ln(1+ ADV)*	*HHI*	*DIS*	*LEV*	*LIQ*
1971-2000	Stock	abs. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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 VI

Fama-MacBeth Cross-Sectional Multivariate Regressions of Volatilities on IT: Foreign Exposure and Diversification

Regressions are estimated with WLS over a cross-section of industries for each year. Observations are weighted by industry shares of market capitalization, sales, and total assets for regressions explaining volatility measures based on stock returns, real sales growth rates, and ROAs, respectively. Dependent variables are absolute firm-specific $(\ln(\sigma_{\varepsilon}^2))$, absolute systematic $(\ln(\sigma_m^2))$, and relative firm-specific $(\ln(\sigma_{\varepsilon}^2)-\ln(\sigma_m^2))$ volatilities of stock returns, real sales growth rates, and ROAs. Systematic volatility is firm-level volatility related to market-wide and industry-wide events. In constructing volatility measures, we use five-year rolling windows and drop firms with fewer than 30 monthly stock return observations or fewer than 15 quarterly sales growth or ROA observations. We further drop industries with fewer than 5 firms or whose IT capital is undefined. Finance industries (SIC code 6000-6999) are omitted. Foreign exposure (*FE*) is the ratio of foreign sales to domestic plus foreign sales. Firm diversification (*SEG*) is the average number of two-digit segments. Since geographic and business segment information in COMPUSTAT is available only from 1985 on, and undergoes a major change in FASB segment reporting standards in 1998, and since we construct five-year averages of the variables, the sample period is restricted to 1989-1997. Since our volatility measures are constructed using five-year rolling windows, we use five-year averages of all control variables. Average coefficients are calculated as in Fama-MacBeth with *t*-statistics adjusted for autocorrelation and heteroskedasticity using the method of Newey and West (1987) as modified in Pontiff (1996). Coefficient estimates of intercepts are not reported. 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+ RD)*	*ln(1+ ADV)*	*HHI*	*DIS*	*LEV*	*LIQ*	*FE*	*SEG*
Stock abs. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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. firm.	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 VII
Fama-MacBeth Cross-Sectional Regressions of Volatility Growth on IT

In this table, we test whether industries with high IT intensity exhibit faster subsequent volatility growth. Dependent variables (ΔVOL) are five-year difference in each volatility measure between year t and $t+5$. VOL is absolute firm-specific $(\ln(\sigma_\varepsilon^2))$, absolute systematic $(\ln(\sigma_m^2))$, or relative firm-specific $(\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2))$ volatility in year t. Systematic volatility is firm-level volatility related to market-wide and industry-wide events. IT is IT intensity in year t for each industry. Since our volatility measures are constructed using five-year rolling windows, we use the five-year average of IT intensity. Regressions are estimated with WLS over a cross-section of industries for each year. Observations are weighted by industry shares of market capitalization, sales, and total assets for regressions explaining growth in the volatility of stock returns, real sales growth rates, and ROAs, respectively. In constructing volatility measures using five-year rolling windows, we drop firms with fewer than 30 monthly stock return observations or fewer than 15 quarterly real sales growth or ROA observations. We further drop industries with fewer than 5 firms or whose IT capital is undefined. Finance industries (SIC code 6000-6999) are omitted. Average coefficients are calculated as in Fama-MacBeth, but t-statistics are adjusted for autocorrelation and heteroskedasticity using the method of Newey and West (1987) as modified in Pontiff (1996). Coefficient estimates of intercepts are not reported. Coefficients significant at 10% or better are in boldface.

(t+5) Period	Volatility	Measure	Adjusted R^2	Number of Industries	*ln(IT)* Estimate	Adj. *t*-stat	*VOL* Estimate	Adj. *t*-stat
1976-2000	Stock	abs. firm.	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. firm.	0.376	41.240	**0.060**[a]	5.077	**-0.738**[a]	-10.286
	Sales	abs. firm.	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. firm.	0.449	37.680	**0.042**[b]	2.441	**-0.892**[a]	-15.791
1976-1983	Stock	abs. firm.	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. firm.	0.405	40.750	**0.092**[a]	20.965	**-0.829**[a]	-9.297
	Sales	abs. firm.	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. firm.	0.390	33.875	-0.012	-1.485	**-0.820**[a]	-21.387
1984-2000	Stock	abs. firm.	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. firm.	0.362	41.471	**0.045**[a]	3.445	**-0.695**[a]	-8.634
	Sales	abs. firm.	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. firm.	0.477	39.471	**0.068**[a]	7.555	**-0.925**[a]	-12.174
(ROA) 1986-2000	ROA	abs. firm.	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. firm.	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.