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CREATIVE DESTRUCTION AND FIRM-SPECIFIC PERFORMANCE

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Creative Destruction and Firm-Specific Performance

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Abstract

We investigate underlying factors that explain increases in the heterogeneity of firm-specific stock returns and fundamentals. Heterogeneity is significantly higher in traditional manufacturing and non-manufacturing industries that are more information technology (IT) intensive in our sample period. We hypothesize that IT is associated with creative destruction, which widens the performance difference between winner and loser firms. Our results suggest recent findings of rising firm-specific variation in U.S. stocks may partially reflect an accelerating pace of creative destruction; and of greater firm-specific variation in richer and faster growing countries may, in part, be due to more intensive creative destruction in those economies. They thus support the approach to endogenous growth theory in Aghion and Howitt (1992, 1998), Aghion *et al.* (2004, 2005), and Acemoglu *et al.* (1997, 2003, 2005).

Keywords: Information Technology, Firm-Specific Variation, 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.

1. Introduction

We propose that the rapid diffusion of *information technology* (IT) across the U.S. economy in recent decades induced a tremor of creative destruction. Schumpeter (1912) argues that economic growth arises from creative destruction: creative firms adopt *new technologies*, thereby destroying stagnant firms. This necessarily widened the performance gap between winners and losers, increasing performance heterogeneity among firms.

Consistent with this, we find greater firm-specific variation in the stock returns and fundamental performance measures of firms in US industries with higher cumulative investment in IT, even after controlling for other important industry characteristics.

Our sample is all traditional US manufacturing and non-manufacturing industries. By this we mean that we drop “dot.com” industries – those whose main activities are the manufacture or use of information technology. We explore the effects of IT investment on industries like automobile parts, mining, petroleum refining, and synthetic fibres.

Our bottom line is that widening firm specific variation in stock returns and fundamental performance measures often reflects widening gaps between winner and loser firms. We present evidence linking investment in information technology to these gaps, and propose that greater firm-specific performance variation reflects intensified creative destruction, although other factors may clearly be at work as well.

The paper is structured as follows. Section 2 describes previous work for which this paper provides a common explanation. Section 3 describes the construction and characteristics of our industry-level IT variable. Section 4 reports regression results on the relationship between IT and variation measures, and Section 5 concludes.

2. Background and Implications

This section reviews key findings regarding firm-specific variation. It then summarizes current thinking on the role of IT in developed economies. Finally, it explains how the findings of this study clarify both literatures.

2.1 Firm-Specific Returns

Our results suggest a common explanation for several empirical regularities regarding firm-specific stock returns variation.

First, individual stocks in more highly developed countries exhibit higher firm-specific returns variation. Morck *et al.* (2000) show that individual stocks exhibit greater firm-specific return variation in higher income countries. Jin and Myers (2004), Li *et al.* (2004), and others confirm this over broader sample periods. Durnev *et al.* (2004b) link

greater firm-specific returns variation to faster economic growth, after controlling for initial levels of income, capital, and human capital.

Morck *et al.* (2000) relate greater firm-specific variation to institutions reflecting the efficiency of the judiciary, the absence of corruption, and the general absence of corruption. Jin and Myers (2004) develop a theory of greater corporate transparency leading to more efficient capitalization of firm-specific information into individual stock prices inducing greater firm-specific variation in earnings, and present supporting cross-country empirical evidence. They propose that the institutional variables Morck *et al.* (2000) use proxy for the transparency of corporations to public investors. Ozoguz (2004) develops a promising alternative theory along similar lines.

Consistent with the importance of transparency, Durnev *et al.* (2003) show that current stock price changes better predict future earnings changes in US industries whose stocks exhibit greater firm-specific variation. Also consistent with this view, Fox *et al.* (2003) show that firm-specific variation rose significantly in US stocks affected by a major accounting reform, but not in other stocks. Finally, Huang (2004) finds higher idiosyncratic stock return variation correlated with economic growth in countries whose investors exhibit greater uncertainty aversion.

Li *et al.* (2004) empirically link increases in firm-specific stock return variation to increased openness to global capital markets, and argue that such openings kick start local financial systems.

La Porta *et al.* (1999) show that the institutional variables Morck *et al.* (2000) link to greater firm-specific stock returns variation are also highly correlated to measures of the development of a country's financial systems. Consistent with the emphasis by Jin and Myers (2004) on transparency, La Porta *et al.* (2004) find high standards of corporate disclosure to be especially important in promoting the development of a country's financial system. Wurgler (2000) confirms these linkages, reporting greater heterogeneity in individual stock returns in countries with more efficient financial systems.

All of the above work links greater firm-specific returns variation with better institutions, especially those associated with financial development.⁵

2.2 Information Technology

The intensity of IT investment in an industry is a reasonable proxy for the pace of creative destruction.

First, IT is associated with faster industry growth.⁶ Using a growth accounting framework, Oliner and Sichel (2000) and Jorgenson (2001) show that growth in IT

⁵ Wei and Zhang (2004) argue that managers take actions to increase share price volatility to raise the values of executive stock options. This seems plausible in the United States, but is unlikely to explain the cross country results of Morck, Yeung and Yu (2000), Jin and Myers (2004), or Li *et al.* (2004), among others.

⁶ 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.

capital stock accounts for nearly half of the acceleration in U.S. productivity growth from the early to late 1990s. Brynjolfsson and Hitt (2003) find similar results at the firm-level.

But more importantly, IT appears to be a *general purpose technology* (GPT), which Bresnahan and Trajtenberg (1995), Helpman and Trajtenberg (1998), and others define as a technology, like electricity in the early 20th century, that spreads to all sectors, permitting innovation in *new processes and products*. A *National Science Foundation* (NSF) survey (2004) asks the managers of about two thousand firms spanning a broad cross-section of industries 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 effect (about 40% for a great effect) *on both*.⁷ Syverson (2004) suggests that IT lets firms in a broad range of industries raise the value of their products by adding intangible qualities to them. In a 1997 survey of Fortune 500 IT managers, Brynjolfsson and Hitt (2003) find that four of their five top reasons for investing in IT involve such intangibles: improving customer services, targeting new customers, improving quality, and improving timeliness. The other reason, reducing total cost, indicates that IT also lets firms innovate in more conventional ways. It is perhaps surprising, given IT's technological roots, that the innovations it triggers mainly involve qualitative product differentiation.⁸

As these innovations occur, some firms win and others lose. The innovations have different value to different firms depending on the distribution of complementary assets.⁹ Schumpeter (1914) argues that only creative entrepreneurs can make use of such new technology, so their firms win and others lose. Hayek (1941) stresses that some firms' managers possess better foresight, and so can better anticipate the economic effects of new technology. Bresnahan *et al.* (2002) stress skilled workers and firm organization. Hobijn and Jovanovic (2001) stress existing assets, arguing that IT is more functional in firms with more modern equipment, and causes younger firms to outperform older ones.¹⁰ Laitner and Stolyarov (2003) stress the human capital of the firm's managers, arguing that IT devalues both old assets and managers familiar with them. More generally, Shleifer and Vishny (1989) argue that managers familiar with old production methods resist new ones, and that this distorts investment decisions, leading to firm underperformance.

As long as the complementary assets are predominantly firm-specific, which seems likely, the IT related innovations they permit should make individual firms' production processes and performance more heterogeneous.

⁷ 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 B.

⁸ Also consistent with this, Mukhopadhyay *et al.* (1997) report that the main effect of IT in the US Post Office is timelier mail processing and Athey and Stern (2002) report that IT decreases response times of emergency response systems. This tendency to increase product values, as opposed to reduce costs, is perhaps unique to IT as a GPT. For example, electricity did not obviously deepen the uniqueness of products in the early 20th century.

⁹ 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.

¹⁰ In another paper, we confirm this conjecture.

2.3 Importance of the Current Study

The key contributions the current study makes is to show that firm-specific variation is higher in US stocks belonging to more IT intensive industries. Given that IT a general purpose technology, capable of spurring creative destruction across a wide range of industries, this finding suggests that higher levels of firm-specific variation in stock returns and other firm performance measures reflect more intense creative destruction, and hence a more extreme performance gap between winner and loser firms.

This linkage casts new light on established empirical results on firm-specific performance variation. In particular,

Creative destruction is more intense in higher income countries

Stocks in countries with higher incomes (Morck *et al.*, 2000) or faster economic growth (Durnev *et al.* 2004b) exhibit higher firm-specific return variation. If this reflects more intense creative destruction, these findings support Aghion and Howitt's (2005) theoretical prediction that creative destruction is more important in higher income countries, and factor accumulation in lower income countries. They also more generally support the theories of Schumpeter (1914), and their formalizations by Aghion and Howitt (1992, 1998), Aghion *et al.* (2004, 2005), and Acemoglu *et al.* (1997, 2003, 2005), which all link economic growth to the rise of innovative firms and the decline of stagnant ones.

Creative destruction is more intense if private property rights are stronger

Morck *et al.* (2000) link greater firm-specific performance heterogeneity to the quality of government, by which they mean an absence of corruption, an efficiency judiciary, and a general respect for the rule of law. La Porta *et al.* (1999) argue that governments that provide these institutional public goods are protecting private property rights

Creative destruction is more intense if corporations are more transparent

Jin and Myers (2004) report greater firm-specific performance variation in countries with more transparent accounting standards. If firm-specific variation reflects creative destruction, these findings link creative destruction to corporate transparency. The findings of Durnev *et al.* (2003, 2004a) and Fox *et al.* (2003), which link corporate transparency to firm-specific variation using US data, can also be reinterpreted in this light.

Creative destruction more intense if financial systems are more developed

Schumpeter (1914) argues that entrepreneurs are often penurious, and so need financing to develop their innovations. He thus argues that a well developed financial system is a prerequisite for growth through creative destruction. Consistent with this, King and Levine (1991) show financial development to be of first order importance to economic growth. Wurgler (2000) links greater firm-specific performance heterogeneity to financial development. La Porta *et al.* (2005) show effective private property rights protection to be a necessary condition for financial development, and La Porta *et al.* (2005) argue that corporate transparency is critical to making investors' *de jure* protection effective. Given these linkages, the findings of Morck *et al.* (2000) and Jin and Myers (2004) can be reinterpreted as indirectly supporting the importance of financial

development to creative destruction. Bris *et al.* (2004), who find greater firm specific variation in countries with more sophisticated financial systems (proxied for by sophisticated short sales and margin rules), can also be reinterpreted in this light as supporting King and Levine (1991) and Schumpeter (1914).

Creative destruction is more intense in more financially open economies

Li *et al.* (2004) show that firm-specific stock return variation rises in emerging economies that become more open to international portfolio investment. Caves (1986) and others argue that openness encourages technology transfer, so the effect Li *et al.* (2004) observe could partially reflect creative destruction associated with that new technology.

Creative destruction can be detected using simple asset pricing models

Roll (1988) laments the low R^2 statistics of standard asset pricing models, and shows their poor fit to be due to high levels of firm-specific variation in US stocks. Morck *et al.* (2000) find much better fits in countries with low *per capita* incomes and weak institutions. If the difference results from more intense creative destruction in the United States and other high income countries, there is no cause for lamentation. Rather, asset pricing models may find a new following among growth theorists, who might find the measures of firm-specific variation these models generate useful as indicators of the intensity of creative destruction. Also, Jin and Myers (2004) point to radically new ways of understanding asset pricing, emphasizing differentially costly information in the tradition of Grossman and Stiglitz (1988).

Other interpretations of firm-specific variation are likely valid too

None of this need undermine the interpretations Morck *et al.* (2000), Durnev *et al.* (2003, 2004a), and Fox *et al.* (2003), Jin and Myers (2004), Li *et al.* (2004), and others attribute to their findings. In particular, the theories of Jin and Myers (2004), as well as those proposed by Huang (2004) and Ozoguz (2004), are probably valid. Certainly, nothing we propose refutes them. Philippon (2003), Gaspar and Massa (2004), and Irvine and Pontiff (2004) may also be correct in attributing greater firm-specific variation to more intense price competition due to institutional changes, openness, or deregulation. And Bennett and Sias (2004) and Brown and Kapadia (2004) may well be right in linking changing corporate demography of industries to increased firm-specific variation. We only suggest that creative destruction might also partially explain their findings.

Our bottom line is that widening firm specific variation in stock returns and fundamental performance measures often reflects widening gaps between winner and loser firms. We present evidence linking investment in information technology to these gaps, and propose that greater firm-specific performance variation reflects intensified creative destruction, although other factors may clearly be at work as well.

3. Construction of Key Variables

This section describes the construction of our measures of firm-specific variation in stock returns and other firm performance measures. It then explains how we measure IT intensity. Finally, the construction of other variables is explained.

3.1 Firm Performance Total Variation Estimates

Our total variation measures of stock returns, sales growth rates, and profit rates are variances of these firm level performance variables measured over a given window and averaged across all firms in an industry.

Estimating mean firm performance variation in an industry requires time series data for each firm. Sales and earnings data are only available quarterly, so a year is insufficient to gauge their variation. We therefore draw data for all our performance measures from five years rolling windows (up to and including the year in question). Three year rolling windows generate qualitatively similar results; as do three year non-overlapping windows. The advantage of longer windows is better estimates for each cross section. The disadvantage is fewer non-overlapping cross sections. Monthly stock data permit non-overlapping annual estimates of stock return total variation as a further robustness check.

Stock returns are total returns: dividends plus capital gains, and are adjusted for splits and stock dividends. We estimate total returns variation using the WRDS combined CRSP-Compustat database. Quarterly sales are deflated by relevant industry price indices. Sales growth each quarter is the current quarter's sales minus those for the same quarter of the previous year divided by the midpoint of the two. To avoid bias due to leverage differences, our profit rates are operating income over assets.

Compustat provides quarterly beginning in 1950, but these are quite sparse until the late 1960s. Also, NASDAQ firms are not included in CRSP until the 1970s. We therefore estimate stock return and sales growth variation for windows ending from 1971 through 2000. Since assets are not reported quarterly until 1976, profit rate variation estimates, also based on Compustat data, use windows ending in 1981 through 2000.

3.2 Firm Performance Variation Decomposition

We wish to study the heterogeneity in firms' performance within each industry. This means we must adjust for common effects shared by all firms in an industry or all firms in the economy. To do this, we follow Roll (1988) in distinguishing 'firm-specific' variation from the sum of market- and industry-related variations. For simplicity, we call the latter sum 'systematic' variation. To obtain this decomposition, we run regressions as in Durnev *et al.* (2004a):

$$[1] \quad r_{i,j,t} = \beta_{i,0} + \beta_{i,m}r_{m,t} + \beta_{i,j}r_{j,t} + \varepsilon_{i,j,t}$$

where $r_{i,j,t}$ is stock return, real sales growth rate, or profit rate for firm i in industry j at time t (t represents month for stock return and quarter for real sales growth rate and profit rate). $r_{m,t}$ and $r_{j,t}$ are the market index and industry indexes, which are value-weighted averages of stock returns, real sales growth rates, or profit rates excluding the firm in question. This exclusion prevents spurious correlations between firm and industry performance measures in industries containing few firms.

The sample for each regression is the window used to draw stock return, sales growth, and profit rate data. Thus, five year windows imply that sales and profit rate regression use 20 quarterly observations, while stock return regressions use 60 monthly

observations.¹¹

The sum of squared residuals, $SSR_{i,j}$, and variation explained by the regression, $SSM_{i,j}$ from each firm-level regression of [1] are aggregated to generate a *mean firm-specific variation*

$$[2] \quad \sigma_{\varepsilon,j}^2 = \frac{\sum_{i \in j} SSR_{i,j}}{\sum_{i \in j} T_i}$$

and mean *systematic variation*

$$[3] \quad \sigma_{m,j}^2 = \frac{\sum_{i \in j} SSM_{i,j}}{\sum_{i \in j} T_i}$$

These sum to the typical firm's total performance variation, illustrated in Figure 1. We construct an aggregate counterpart to the R^2 of regression [1] to measure *systematic as a fraction of total variation* for a typical firm,

$$[4] \quad R_j^2 = \frac{\sigma_{m,j}^2}{\sigma_{\varepsilon,j}^2 + \sigma_{m,j}^2}.$$

3.3 Information Technology Intensity

Industry-level IT data are from *Fixed Reproducible Tangible Wealth* (FRTW), published by the *Bureau of Economic Analysis* (BEA), which lists investment in 61 classes of assets for each two-digit (1987 SIC code) industry.¹² We define *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).¹³

We follow Hall (1990) and construct a real capital stock for each type of IT asset in industry j at time t using a perpetual inventories model, but with asset-specific geometric depreciation at rates δ_i .¹⁴ The stock of type i capital in industry j at time t is

$$[5] \quad K_{i,j,t} = (1 - \delta_i)K_{i,j,t-1} + I_{i,j,t}$$

¹¹ 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 restrictions, which basically means we include all new firms, the statistical significance of the results actually improves somewhat.

¹² See Herman (2000) for a detailed description of the data set.

¹³ 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.

¹⁴ Depreciation rates, from Fraumeni (1997), average 0.31.

We use the Törnqvist index to aggregate these ten types of computer hardware and software into IT capital.¹⁵ Using the same procedure, we define *non-IT capital* as all other asset types.

The IT intensity of industry j at time t is then that industry's stock of IT capital over its total (IT plus non-IT) capital stock,

$$[6] \quad IT_{j,t} = \frac{K_{IT,j,t}}{K_{TOT,j,t}}.$$

We use intensity, rather than current IT investment, because we are interested in how the utilization of information technology affects cross-sectional patterns of variation. Creative destruction plausibly depends not just on current IT investment, but on IT intensity – firms' overall abilities to apply IT to their ongoing businesses.

[Figure 1 about here]

3.4 Observations

The total column heights in the first three panels of Figure 1 plot the three total variation measures through time. The coloring of the columns breaks this into mean firm-specific (white) and systematic (black) variation.

As robustness checks, we also construct medians, 1% winsorized means, and industry sales, assets, and market capitalization weightings. All produce similar upward trends. The major difference is that the profit rate graphs are smoother in the medians and winsorized means, and so more closely resemble those of the other performance measure variations.¹⁶ To ensure that our profit rate measures are not distorted by earnings 'management', we reconstruct them controlling for accruals as in Chan et al. (2001). This too generates qualitatively similar results to those shown.

Several interesting observations emerge from these totals and their decomposition

Firm-specific fundamentals variation rises with stock returns variation

Rising firm-specific fundamentals variation tracks the rising firm-specific variation in stock returns reported by Morck *et al.* (2000) and Campbell *et al.* (2001).¹⁷ Because our robustness checks on medians and equally-weighted measures look similar, rising firm-specific variation is not confined to a few large industries.

Xu and Malkiel's (2003) proposition of noise trading by increasingly important institutional investors cannot thus be a complete explanation. An explanation Morck *et al.* (2000) propose, increasingly efficient capitalization of firm-specific information into

¹⁵ For further details, see Appendix A.

¹⁶ ROA outliers typically have few assets and high profits. Dropping these observations does not affect the regressions, so we retain them.

¹⁷ Gaspar and Massa (2004), Irvine and Pontiff (2004), and Wei and Zhang (2004) independently corroborate this.

share prices, is likewise incomplete.¹⁸ Neither accounts for a rise in fundamentals variation. Note however, that firm-specific stock return variation forms a loose upper bound on firm-specific fundamentals variation. This leaves room for pure noise trading and pure information explanations of the apparent excess firm specific variation of stock returns.

[Table 1 about here]

A Fallacy of Composition

Macroeconomic volatility falls in the OECD economies in recent decades.¹⁹ The literature reviewed above requires explanations of this to permit a simultaneous rise in firm-specific volatility. Figure 1 beclouds explanations like Kahn *et al.* (2001), who link falling aggregate volatility to IT improving inventory, production, and demand planning, reducing firm performance volatility, and so reducing aggregate volatility.

A variant of the Keynesian *fallacy of composition* applies. Aggregate variation is not the simple sum of firm variations. Correlations between firms matter too.²⁰ Obviously, if firms' performance grows less correlated, aggregate volatility can fall even as firm-level volatility rises.

To check this, we aggregate the sales, profits, and market values of all firms in our sample each year and calculate the variations in aggregate sales growth, profit rate, and stock market returns. These all fall through time, consistent with the macroeconomics literature (previous footnote), despite the rising firm level variations reported above.

This provides a microeconomic counterpart to the well-documented *macroeconomic structural break point* in 1984 – see e.g. Kim and Nelson (1999) and McConnell and Perez-Quiros (2000). Figure 1 suggests a contemporaneous microeconomic break point in that year, especially in sales growth variation. Panel A shows mean ratios of firm-specific to systematic variation across all industry-year observations - first for the whole sample period, and then over two sub-periods: 1971-1983 and 1984-2000. The median ratios reported in the table show that firm-specific variation for the whole sample period is almost five times larger than systematic variation in stock returns and about three times larger in real sales growth and profit rate. The divergence between firm-specific and systematic variations becomes more pronounced in the second sub-period in general, especially for stock return variation.

[Figure 2 about here]

¹⁸ Though it is unlikely to be wrong either. Bris *et al.* (2004), Durnev *et al.* (2004a, 2004b), Fox *et al.* (2005), Huang (2004), Jin and Myers (2004), Li *et al.* (2004), Ozoguz (2004), and others also present evidence and theoretical arguments consistent with this being an important partial explanation.

¹⁹ See Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), Stock and Watson (2002), Boivin and Giannoni (2003), and others

²⁰ Variation of aggregate corporate sales growth, a component of GDP growth, $\text{var}(\sum_j w_j \Delta \ln(s_j))$, is the sum of two components: the weighted sum of firm level sales variances, $\sum_j w_j^2 \text{var}(\Delta \ln(s_j))$, and the cross-weighted sum of firm level sales growth covariances, $\sum_j \sum_{k \neq j} w_j w_k \text{cov}(\Delta \ln(s_j), \Delta \ln(s_k))$. If the covariances decline sufficiently, aggregate variation can fall while firm level variation rises.

Firm-specific returns variation bounds fundamentals variation

Figure 2 shows the weighted average R^2 of regression [1], equal to $\sigma_m^2 / (\sigma_m^2 + \sigma_\varepsilon^2)$, falling over time – by about 50% for stock returns and real sales growth.²¹ Since the mid-1970s, the stock returns' average R^2 is lower than those for the other two measures. This might reflect additional factors in stock prices alone – such as increased transparency, as in Huang (2004), Jin and Myers (2004), and Ozoguz (2004), reduced arbitrage costs, as in Bris *et al.* (2004), or possibly increased institutional trading as in Xu and Malkiel (2003).

Firm-specific variation is positively correlated with systematic variation

Panel B of Table 1 shows this, especially for profit rates.²² This suggests that much firm-specific variation is heterogeneous firm reactions to market or industry-wide shocks. Industry wide shocks might include the sudden success of one firm in applying IT to increase productivity.

Information technology looks like a general purpose technology

The bottom panel of Figure 1 graphs the cross-industry distribution of IT intensity, the ratio of the IT capital stock to the total capital stock in 2000. Unsurprisingly, it shows an upward trend, like those of the firm-specific variation measures. Whether the trend are connected or not cannot be inferred reliably from the data in Figure 1, so this question must await the industry-level analysis in the next section.

IT fits as a general purpose technology in that it is high across a broad range of industries. Figure 3 shows that IT investment is substantial across a wide swath of industries. IT accounts for more than four percent of the capital stocks of 27 out of the 45 industries listed. A comparable calculation of R&D capital reveals R&D intensities exceeding four percent in only 6 industries. Further examination shows that R&D assets are highly concentrated within the largest few firms in those industries.²⁴ Figure 4 displays a sequence of histograms, showing the persistence of this broad cross-industry distribution through time.²⁶ This variation provides a natural cross-sectional testing ground for studying the effects of IT on the variations of various performance measures.

[Figures 3 and 4 about here]

²¹ Morck et al. (2000) show this to be so if the weights are $\sigma_m^2 + \sigma_\varepsilon^2$.

²² Although a positive correlation between the independent variable and residual in firm-level regressions produces inconsistent estimators, these correlations are between aggregate measures calculated to represent industry-level average firm-specific and systematic variations. This makes it possible to have a positive correlation between the two measures even if there is no correlation problem in regression [1]. The

²⁴ We use R&D intensity as an additional variable in §4, and estimate it using analogs of [5] and [6], as in Hall (1990). For details, see footnote 38.

²⁶ Jovanovic and Rousseau (2003) find that the recent diffusion of IT across industries was slower than that of electrification in the early twentieth century.

4. Performance Heterogeneity and Information Technology

We now test whether industries with higher IT intensity exhibit greater firm-specific performance variation: first in bivariate regressions, then in multiple regressions controlling for industry characteristics. Finally, we examine causation.

4.1 Econometric Framework

Time-series patterns of IT intensity and performance variation suggest a possible relationship. However, both exhibit strong time trends (IT intensity in many industries contains a unit root.), inducing well-known inference problems. Thus, we focus on cross-sectional relationships between IT intensity and performance variation.

We run weighted least square (WLS) regressions for each year and report Fama-Macbeth coefficients and t -statistics.²⁷ Fama-Macbeth coefficients are the time-series averages of the coefficients of cross-section regression run separately for each year. The associated t -ratios are based on the empirical time series standard deviations of these cross section estimates. Fam-Macbeth can thus be considered a bootstrapping approach to panel estimation, where each cross section is treated as a draw from the whole sample. Since cross section observations are serially correlated, simple standard deviations so estimated would provide biased t statistics. We therefore follow Pontiff (1996) and apply the method of Newey and West (1987) to estimate standard deviations of our coefficients.²⁸ This corrects for serial correlation in the estimated parameters, including that arising from overlapping rolling windows in the construction of some of our variables.

We exclude financial industries (1987 SIC codes from 6000 to 6999) because their accounting data (such as sales and profit rate) are incompatible with that in other industries. Thus, the maximum number of industries is 50, consisting of 20 manufacturing and 30 non-manufacturing industries.²⁹ We also discard industries containing fewer than 5 firms, and industries whose IT stock is not defined.

The variation measures used as dependent variables in the regressions below are simple transformations of those in Figure 1. To obtain near normal dependent variables, we apply logarithmic transformations to obtain *absolute firm-specific variation*, $\ln(\sigma_{\varepsilon,j}^2)$, and *absolute systematic variation*, $\ln(\sigma_{m,j}^2)$ for stock returns, sales growth, and profit rate in each industry j in each year. Since R^2 is bounded within the unit interval and highly skewed, we apply a logistic transformation, as in Durnev *et al.* (2004a), to obtain *relative firm-specific variation*

$$[7] \quad \psi_j = \ln\left(\frac{1-R_j^2}{R_j^2}\right) = \ln(\sigma_{\varepsilon,j}^2) - \ln(\sigma_{m,j}^2).$$

for each performance measure in each industry j each year. Relative firm-specific

²⁷ 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.

²⁸ This dramatically reduces the t -ratios relative to OLS, fixed effects, or standard Fama-Macbeth procedures. We report these results because they are the most conservative of possible approaches.

²⁹ The number of industries used in this paper is almost the same as in Hobijn and Jovanovic (2001) and Stiroh (2002).

variation gauges the importance of absolute firm-specific variation relative to absolute systematic variation.

[Table 2 about here]

4.2. Bivariate Results

Table 2 presents bivariate regressions showing that absolute firm-specific variation in stock returns, sales growth rates, and profit rate is strongly positively correlated with IT intensity. This holds with regressions from 1971 through 2000, 1971 through 1983, and 1984 through 2000. Profit rate variation regressions are available only for the 1984 through 2000 sub-period because of the absence of quarterly data for earlier years.

IT intensity is also positively correlated with absolute systematic stock return variation. However, its correlation with absolute firm-specific returns variation is larger, resulting in a positive significant correlation with relative firm-specific stock return variation over the full sample period and the two sub-periods.

IT intensity is also positively related to relative firm-specific sales growth variation, but only in the second sub-period. In the first sub-period, the correlation of IT with absolute systematic variation is as large as that with absolute firm-specific variation.

The results for profit rate variation are the weakest of the three. The correlation of IT with absolute firm-specific profit rate variation is smaller than IT's correlation with absolute systematic profit rate variation, so relative firm-specific profit rate variation ends up negatively correlated with IT investment.

Overall, IT intensity is not more highly correlated with variation in the post-1984 sub-period than earlier – except in the case of relative firm-specific sales growth variation where the relationship is insignificant in the earlier sub-period. The greater firm-specific variation in later years is due to greater IT intensity, not a larger effect of one percent increase in IT intensity.

The regressions in Table 2 generally have respectable adjusted R^2 s, with those using stock returns typically the highest. A weaker relationship with sales growth and profit rate variations might reflect data quality - quarterly observations of sales growth and profit rate versus monthly data for returns.

Figure 6 graphs these relationships in 2000. High firm-specific variation and high IT intensity industries 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 variation is economy-wide, not just confined to a specific group of industries such as dotcoms.

4.3. Control Variables for Multiple Regressions

This section introduces other industry characteristics that might affect cross-industry variation in firm-specific variation. In each regression, we match the estimation windows of our variation measures to those of our controls. Thus, if we use five-year overlapping windows to estimate the former, we use the same windows to estimate the control variables. Details about more technical aspects of construction of some control variables are relegated to Appendix A. The next section explores multiple regressions that re-examine the relationship between variation and IT controlling for these characteristics.

Mechanical Explanations

We first consider some purely mechanical reasons for differences in the variation of firm performance. These are average leverage, average liquidity, the number of firms in the industry, and their average degree of diversification - across industrial and geographically.

- *Leverage*

For purely mechanical reasons, firms with higher leverage have more volatile earnings and stock returns, though not more volatile sales growth, all else equal. Consequently, industries whose firms are typically 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. In this and all other control variables constructed as ratios of financial data, we divide industry aggregate by industry aggregate.

- *Liquidity*

Myers and Majluf (1984) argue that firms retain cash cushions – liquidity reserved for getting through bad times. All else equal, firms with such reserves should be less adversely affected by negative shocks, firms specific or systematic, than otherwise comparable firms.

Liquidity is the ratio of industry total current assets (annual item 4) to total current liabilities (annual item 5) for each industry.³⁰

- *Industry Population*

Firms in industries containing more firms might have more firm-specific performance variation for a variety of reasons. More populous industries might encompass more heterogeneous production methods, more varied corporate governance, or more geographically diverse economic environments. More populous industries, all else equal, are also more likely to provide observations in the extreme tails of performance distributions.

We measure the population of each industry with the logarithm of the number of firms it contains in a given year.

- *Industrial Diversification*

Firms that have operations in more industries, all else equal, should track the market more closely and their primary industry index less closely. In addition, Agarwal *et al.* (2004) argue that greater investor uncertainty after firms diversify into new lines of business increases stock return variation and Morck *et al.* (1989) and others present investors view diversification *per se* as evidence of firm-specific governance problems.

We therefore control for average firm-level diversification using the industry mean logarithm of the number of two digit industries for which each firm

³⁰ 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.

reports positive sales. These data are from Compustat industry segment data.³¹

- *Geographic Diversification*

Multinational firms are subject to risks that little affect many purely domestic firms: exchange rate fluctuations, foreign demand shocks, and the like. But their foreign sales can also mitigate the effects of domestic shocks on their performance.

To measure foreign exposure, we use the ratio of industry foreign to total sales, from Compustat.³²

Of course, all else might not be equal, for managers adopt strategies of leverage, liquidity, entry, and diversification given their expectations about the future. If firms in more volatile industries are thus less leveraged, more liquid, or more diversified, we might observe no relationship between leverage and our performance variation measures. Also, if low liquidity or high debt result from recent investment in IT, including these variables may improperly detract from IT intensity. If more populous industries encompass more variegated sub-industries, they might include firms moving in new directions unanticipated at the demarcation of SIC codes many years ago. This means controlling for the number of firms in an industry may bias the coefficient on IT intensity downward.

Given these considerations, we run all our results both with and without these control variables. Robustness to this implies that mechanical artefacts associated with leverage, liquidity, or industry population are unlikely to underlie our results.

In addition to purely mechanical effects, we must control for variables associated with alternative explanations of firm-specific performance variation differences.

Increased Competitive Pressure

One such set of alternative, modeled by Philippon (2003), holds that more intense price competition magnifies the importance of small firm-specific performance shocks. Cutthroat competition can turn a minor setback into a bankruptcy and a minor competitive edge into sustained dominance. In a similar vein, Gaspar and Massa (2004) argue that market power cushions firms against shocks and reduces investors' information uncertainty.

Consistent with this, Gaspar and Massa find lower firm-specific volatility in firms with potential market power. Comin and Mulani (2003) and Irvine and Pontiff (2004) also report lower firm-specific variation in deregulated industries. The latter also find greater firm-specific variation in sectors subject to stiffer international trade pressure, again consistent with Philippon (2003) and Gaspar and Massa (2004).

³¹ More detailed breakdowns of firms' operations by industry are available from 1985 on, but major changes in segment reporting standards in December 1998 (when SFAS 131 superseded FASB 14) and well-known accounting problems with the earlier data render their use problematic.

³² The problems discussed in the previous footnote also affect geographic segment data. In addition, some firms report geographic data by country, while others report it by region – i.e. Europe, Latin America, Asia. This makes the number of geographic segments an unsuitable variable. We therefore use foreign sales, but because of the change in accounting rules in 1998, exclude 1998 and subsequent data. Our data range thus differs from that for other variables. Restricting our regressions accordingly does not qualitatively change our results.

We therefore control for direct measures of price competition intensity using:

- *Price Competition*
We calculate a sales-based Herfindahl-Hirschman Index for each industry in each year. These data are based on total firm sales for each company listed in Compustat. We therefore overstate concentration because we miss sales by unlisted firms, sales by subsidiaries of firms listed abroad, sales by firms with core businesses in other industries, and sales in other industries by firms whose core operations are in the industry in question.
- *Import Penetration*
For each industry in each year, we take imports as a fraction of total sales. We follow Irvine and Pontiff (2004) in using data from the National Bureau of Economic Research, as described in Feenstra, Romalis, and Schott (2002).

Price competition need not pre-empt a role for IT. IT based innovation might ultimately spur price competition. For example, Brown and Goolsbee (2002) show internet sales significantly reducing individual life insurance premiums. Or, heightened competition might induce corporate managers to invest in innovation in a gamble to gain any edge over competitors.

The competition measures above also might proxy for the pace of innovation. For example, Caves (1984) argues that international openness attracts foreign innovations to domestic markets, often via foreign direct investment. This perhaps explains why Li et al. (2004) find countries opening to global capital flows, more than international trade, raising firm-specific stock return variation.

Either consideration suggests controlling for price competition might bias downwards the coefficients of IT intensity. But if IT remains significant nonetheless, it is unlikely to be proxying for pure price competition.

Industrial Demography

Pastor and Veronesi (2003), Fama and French (2004), Bennett and Sias (2005), and Brown and Kapadia (2005) all link rising firm-specific variation in the United States to a rising importance of new listings in its stock markets.

To control for the importance of new firms, we measure the demography of each industry thus:

- *Average Age as a Listed Firm*
This is the number of years since the firm first appeared in the CRSP monthly database. Our first industrial demography control is the logarithm of the mean of this across all firms in an industry at a given time.
Since these data begin in the 1920s for NYSE and AMEX listed firms, we underestimate the age of firms listed before then. NASDAQ listed firms were added to CRSP beginning in the 1960s, so we again miss some of the early listed firms on that market. This measure also misses firms listed on regional or foreign exchanges that later listed on the NYSE, AMEX, or NASDAQ. Finally, it can underestimate the age of firms newly relisted after corporate control transactions.

- *Average age of Physical Assets*

We gauge the average age of a firm's capital assets, as in Hall (1990), by the ratio of accumulated depreciation (gross less net property, plant and equipment) to current depreciation and amortization.³³ Our second variable is the logarithm of the mean of this variable for all firms in an industry at a given year.

If accounting depreciation faithfully tracks economic depreciation, this is a valid measure of firm age. Since the two correspond only loosely, this measure is noisy.

- *Firm Size Distribution*

The distribution of firm size may reflect pre-existing heterogeneity among firms, which could affect performance variation.

We use the standard deviation of the logarithm of firm market capitalizations, sales, and total assets to measure the dispersion in firm size for each industry.

The two age measures are highly correlated ($\rho = 0.64$, $\pi \ll .01$), and generate similar results in our multiple regressions. Given the problems associated with the determining the date of first listing, we present results using the average age of physical assets and use the former variable as a robustness check.

The economics of why more small or new firms should raise firm-specific performance variation are not fully understood. Perhaps they are more vulnerable to small negative shocks, as in Philippon (2003), Gaspar and Massa, Comin and Mulani (2003), and Irvine and Pontiff (2004). Alternatively, Schumpeter (1914), Aghion and Howitt (1996), and others argues that innovation triggers creative destruction, where innovative new firms arise to displace staid old ones. New firms are usually also small, at least initially. Empirical work by King and Levine (1993), Fogel, Morck, and Yeung (2004), and others supports this view.

If the first explanation is correct, including corporate demography measures is appropriate to reduce noise in our regressions. But if the second is correct, corporate demography is an alternative measure to IT intensity of the pace of innovation and creative destruction, and including these control variables may bias downwards the coefficient of IT intensity. In this case, the persistence of a significant coefficient is strong evidence of a link between IT intensity and firm-specific variation, and the joint significance of IT intensity and demography would be a more appropriate test for a link between firm-specific performance variation and creative destruction.

Other Measures of Innovation

More generally, financial edges that separate winners from losers in creative destruction are thought to involve investments in intangible assets such as technology and reputation.

³³ Compustat item 7 less item 8 all divided by item 14.

³⁸ The industry sum of Compustat annual item 60 over the sum of the products of items 25 and 199.

To investigate the importance of innovation more broadly, we consider

- *Book to Market Ratio*

In an efficient stock market, intangible assets are reflected in firms' market values, but are often not capitalized for accounting purposes and so are not reflected in book values. This makes book to market ratios useful proxies for the general presence of intangible assets.

We construct book to market ratios as the industry aggregate book value of common equity divided by the aggregate market value of common stock at companies' fiscal year ends.³⁸

- *Research and Development intensity*

Technological edges resulting from R&D spending, as well as from IT investment, might fuel creative destruction. We therefore consider R&D intensity as an additional variable.

Since R&D is expensed, not capitalized, we follow Chan et al. (2001) and construct R&D intensity from past R&D in a precise analog to the construction of IT intensity in [5] and [6].³⁹

- *Marketing Intensity*

Reputation edges result from advertising spending, among other things, and might also fuel creative destruction. We therefore consider advertising intensity as a partial measure of reputation capital.

Advertising intensity is constructed in the same way as R&D intensity.⁴⁰

We use IT intensity to measure the pace of creative destruction in different US industries because IT is thought to be a GPT, and so to induce creative destruction across a wide swath of industries. R&D and advertising spending, in contrast, are narrowly concentrated in a handful of industries and, within those, in the largest firms. Book to market ratios are imperfect proxies for intangible assets because they capture growth opportunities as well (Cao et al.; 2004) and because of endogeneity problems: Market values convey information to managers and this presumably affects their decisions.

The concentration of R&D and advertising in a few industries, mainly in the manufacturing sector, raises the concern that these variables might proxy for other characteristics those industries share. We therefore also consider regressions with a manufacturing dummy as a control variable, and this does not qualitatively change our results.

³⁹ In the analog to [5], we calculate *R&D capital stock* by deflating R&D (Compustat annual item 46) at the GDP deflator and assuming 20% depreciation. In the analog to [6], *R&D intensity* is the R&D capital stock over property, plant, and equipment (item 8), deflated by the BEA FRTW 2-digit industry index.

⁴⁰ Advertising expense is Compustat annual item 45. The procedure and assumptions are identical to those in the previous footnote.

Other Control Variables

Investment in conventional capital assets might also increase firm-level performance variation by increasing uncertainty about firms' future cash flows. Or, increased variation might discourage firms from making capital expenditures. Which effect dominates is an empirical question. Regardless, we include the investment rate in non-IT capital as an additional control.

- ***Investment in Non-IT Capital***

We construct the 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).

[Table 3 about here]

Table 3 displays time-series averages of simple cross-sectional correlation coefficients between the above controls and between them and IT intensity. 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.

[Tables 4 and 5 about here]

4.4. Multiple Regressions

Table 4 describes multiple regressions of variation on IT intensity controlling for all the above industry-level control variables. Since business and geographic segment data are unavailable for earlier years, the foreign exposure and firm diversification measures are not included. Table 5 reports analogous regressions including these two additional controls, but dropping the earlier years. The key results from Tables 4 and 5 are as follows.

1. IT is significantly positively correlated with both absolute and relative firm-specific variations. The anomalous negative sign on relative firm-specific profit rate variation in Table 2 is now flipped. 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 variations. In fact, IT is the only variable that explains both variation measures with a consistently significantly positive sign throughout the sample period.

2. Despite the patterns evident in the bivariate regressions above, IT intensity is not significantly related to absolute systematic variation when we include the controls, especially R&D intensity.⁴⁸ This is because the component of IT related to absolute systematic variation is highly correlated with R&D intensity. IT attracts a positive and

significant coefficient in regressions explaining relative firm-specific stock returns and sales growth variations; but R&D does not. Overall, IT seems related to firm-specific variation, while R&D appears related to systematic variation. Appendix B explores this further by discussing different characteristics of IT and R&D that might explain this.

3. 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 variation measures. When we include more controls, the sign becomes positive for the absolute variation measures. Herfindahl-Hirschman Index also changes its sign during our sample period.⁴⁹ This instability and the multiple interpretations possible for some controls make interpreting their coefficients and significance levels problematic.

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

Including firm diversification and foreign exposure in the regressions of Table 5 barely changes the signs and significance of IT intensity in explaining all the variation measures.

4.5. Robustness Checks

We repeat our empirical exercise in several different ways. None of these alternative approaches qualitatively changes our results - by which we mean that the patterns of signs and significance in the coefficients of IT intensity is preserved. First, we check whether the *de minimus* restriction on the number of observations used in calculating our variation 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 variation measure. Third, we check whether the inclusion or exclusion of footnote stamped data from COMPUSTAT alters the results. Footnotes flag unusual events, such as mergers, accounting changes, discontinued operations, and the like. Such events can render sales growth or profit rate estimates problematic. 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. Sixth, we repeat our analysis using windows of various lengths. Three year rolling windows generate results that are almost identical to those shown. One year windows, feasible only for stock return variation estimates, also generate results qualitatively similar to those in the tables. Five year non-overlapping windows permit too few cross sections to permit Fama-Macbeth techniques, however standard OLS regressions on each cross section generate coefficients qualitatively similar to those shown. Three year non-overlapping windows

⁴⁹ Competition increases absolute firm-specific variation only in the first sub-sample only. Even in this case, competition decreases relative firm-specific variation.

likewise yield standard OLS regressions on each cross section that are qualitatively similar to the results shown.

4.6. Endogeneity

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

The converse, that high firm-specific variation causes IT intensity, might follow if more volatile industries invest more in IT capital to decrease variation through, for example, better inventory management. This implies declining firm-level variation 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 variation 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 variation, or raises it, we use the following regression:

$$[8] \quad \Delta Vol_{j,t+1} = \alpha + \beta \ln(IT)_{j,t} + \gamma Vol_{j,t} + \varepsilon_{j,t+1}$$

where $\Delta Vol_{j,t+1}$ is a five-year difference of one of our variation measures⁵⁰ (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 variation measure of industry j at time t . We include $Vol_{j,t}$ to control for initial differences in the level of variation. If IT intensity raises firm-specific variation, β should be positive in the absolute and relative firm-specific variation specifications of [8]. If high variation induces IT investment aimed at reducing variation, we expect a negative β . If IT investment is correlated with pre-existing high variation, β should be insignificant.

The regression specification in [8] resembles those used in the economic growth literature, for example in Barro and Sala-i-Martin (1995). In this literature, special attention attaches to $Vol_{j,t}$ because, in cross-sectional regressions, the residuals, $\varepsilon_{j,t+1}$, 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 variation 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 variation or relative firm-specific variation could be vulnerable to this problem. Consequently, caution is warranted in interpreting results for these two variation measures.

[Table 6 about here]

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

Table 6 reports Fama-Macbeth regression coefficients for [8], along with t -statistics robust to serial correlation and heteroskedasticity. Absolute firm-specific variation rises *following* periods of high IT intensity.⁵¹ The sole exception is absolute firm-specific stock return variation 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 variation also rises subsequent to high IT intensity, most markedly in the second sub-period. Relative firm-specific variation in profit rate is insignificant in the second sub-period, mirroring our earlier cross-sectional bivariate regression results. Note also that γ is negative. Thus the intensity of creative destruction (measured by firm-specific variation) tends to decrease over time, all else equal, in the absence of sustained IT investment.

These findings are consistent with IT intensity ‘causing’ higher variation, and difficult to reconcile with IT intensity being either aimed at reducing variation or an artefact of pre-existing heterogeneity.

5. Conclusion

Higher firm-specific variation in individual firms’ stock returns, real sales growth rates, and profit rates is associated with more intensive investment in information technology (IT). These findings are robust to a wide range of variable construction techniques, 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. IT intensity is the only variable that consistently explains both firm-specific variation (absolute firm-specific variation) and the ratio of firm-specific to systematic variations (relative firm-specific variations) of stock returns and fundamentals throughout our sample period.

All this is consistent with IT serving as a general purpose technology that induces a wave of innovation across many different industries.⁵² This innovation takes the form of creative destruction, as in Schumpeter (1914), with some firms taking better advantage of IT advances than others. A growing gulf between successful and unsuccessful IT adopters raises heterogeneity in firm performance within industries. This manifests as greater firm-specific variation in stock returns and fundamentals, but is consistent with lower aggregate variation because firm-specific variation cancels out in the aggregate measures. This *fallacy of composition in variation* effect is greater in industries that invest more heavily in IT.

Our findings help explain why greater firm-specific variation is related to better developed financial systems and better economy performance, as reported in Morck *et al.*

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

⁵² R&D intensity behaves quite differently from IT intensity, perhaps reflecting IT’s nature as a general purpose technology. R&D may measure a different sort of investment in innovation more aligned with the economies of scale arguments in Schumpeter (1942) or Romer (1986).

(2000), Wurgler (2000), Bris *et al.* (2004), Fox *et al.* (2003), and Durnev *et al.* (2004a,b). Better developed financial systems plausibly permit entry and hasten creative destruction, which raises average living standards. Our results also help understanding seemingly contradictory results on the effect of variation on economic growth. For example, Durnev *et al.* (2004b) find faster growth in countries whose stock returns display greater firm-specific variation while Ramey and Ramey (1995) find countries with higher aggregate variation growing slower.⁵³ He *et al.* (2004) also link faster GDP and productivity growth to an increased turnover in lists of countries' leading firms. Firm turnover is an extreme form of firm-specific performance heterogeneity, where losers drop out, so this result can be interpreted in the same spirit as ours.

Our findings also provide insight into other recent work on firm-specific performance heterogeneity. Philippon (2003), Gaspar and Massa (2004), and Irvine and Pontiff (2004) emphasize increased competition as underlying recent increases in firm-specific variations. If increased competition means hastened creative destruction, rather than tighter pricing margins, we concur. Agarwal *et al.* (2004) presents evidence, along these lines, that when 'bricks and mortar' firms enter eCommerce, their firm-specific variation increases, though only after mid 1998. One interpretation of this finding is that winners and losers in the race to enter eCommerce became evident once the size of the Internet reaches a critical threshold.

Finally, the increase we observe in firm-specific returns variation outpaces those in firm-specific sales growth and profit rate variation. Morck *et al.* (2000), Bris *et al.* (2004), Durnev *et al.* (2004a), Fox (2003), Huang (2004), Jin and Myers (2004), and Ozoguz (2004) present evidence and models consistent with interpreting firm-specific variation as a measure of stock market transparency. This outpacing leaves open the possibility of transparency as a second parallel explanation. Indeed, the two may be intertwined, for more transparent stock markets might permit more intensive investment in new technologies, such as IT, by making the capital needed to finance it cheaper. That stock market variation tracks the variations of fundamentals limits, but need not eliminate, other explanations of individual stock price variation.

⁵³ Ramey and Ramey interpret their finding as consistent with decreased uncertainty spurring investment, as in Pindyck (1991).

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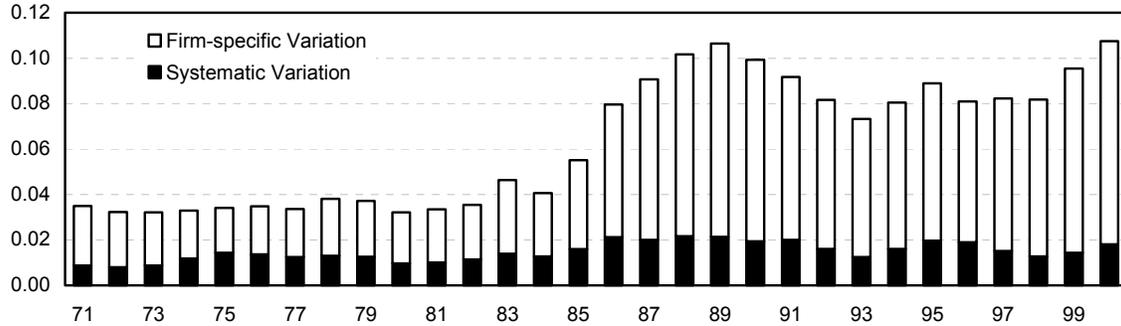
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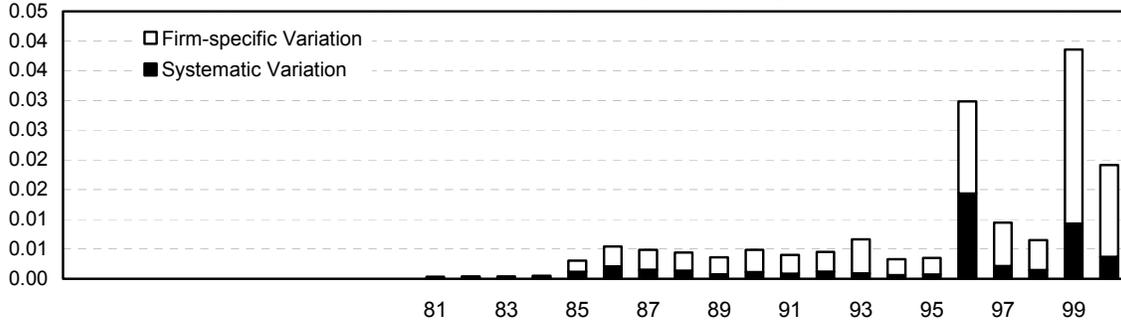
Figure 1. Firm Performance Total Variation and Decomposition

Mean total variation in firm-level performance decomposed into mean systematic (related to industry and economy factors) and mean firm-specific variation. Estimates use quarterly data from five year rolling windows ending in the year indicated on the horizontal axis.

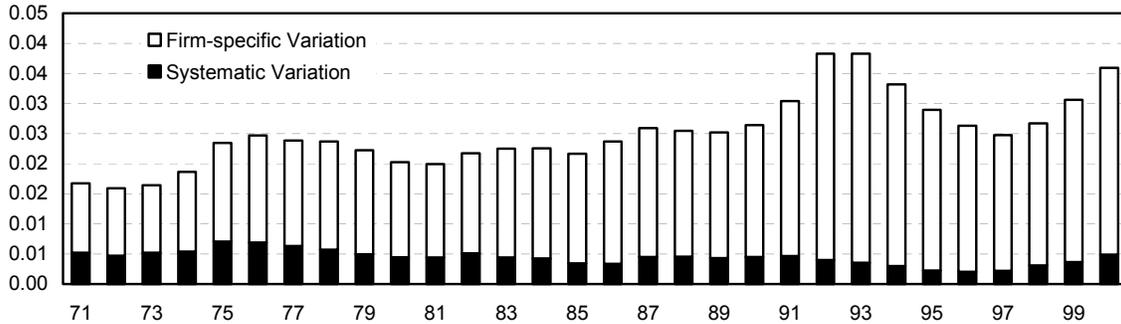
Panel A. Performance Measures as Quarterly Sales Growth



Panel B. Performance Measured as Quarter Profitability (Operating Income over Assets)



Panel C. Performance Measured as Monthly Stock Returns, Including Dividends



Panel D. Information Technology Assets as a Fraction of Total

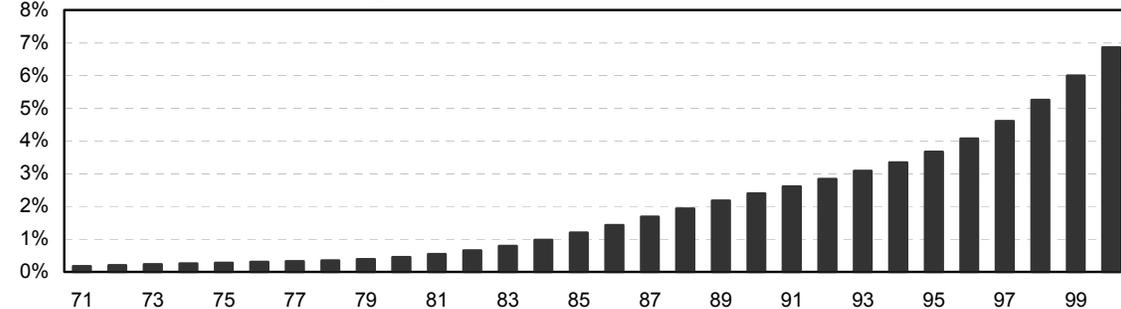


Figure 2. Firm Performance Variation Fractional Decomposition
 Systematic variation in firm-level performance as fraction of total variation, or R squared. Estimates use quarterly data from five year rolling windows ending in the year indicated on the horizontal axis.

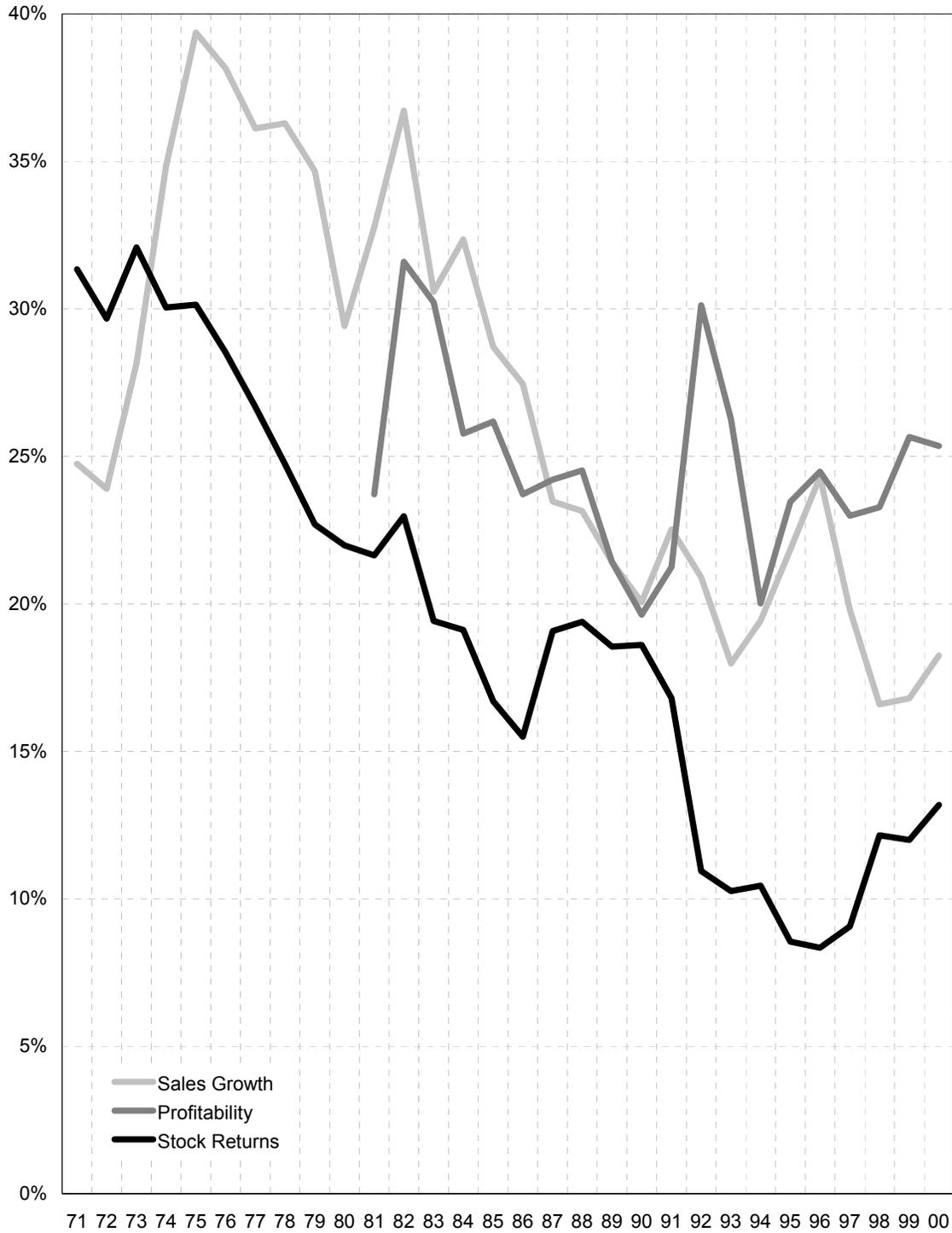


Figure 3. The Distribution of IT Assets Across Industries in 2000

IT intensity is real IT investment using a perpetual inventory model with a depreciation rate of 20%.

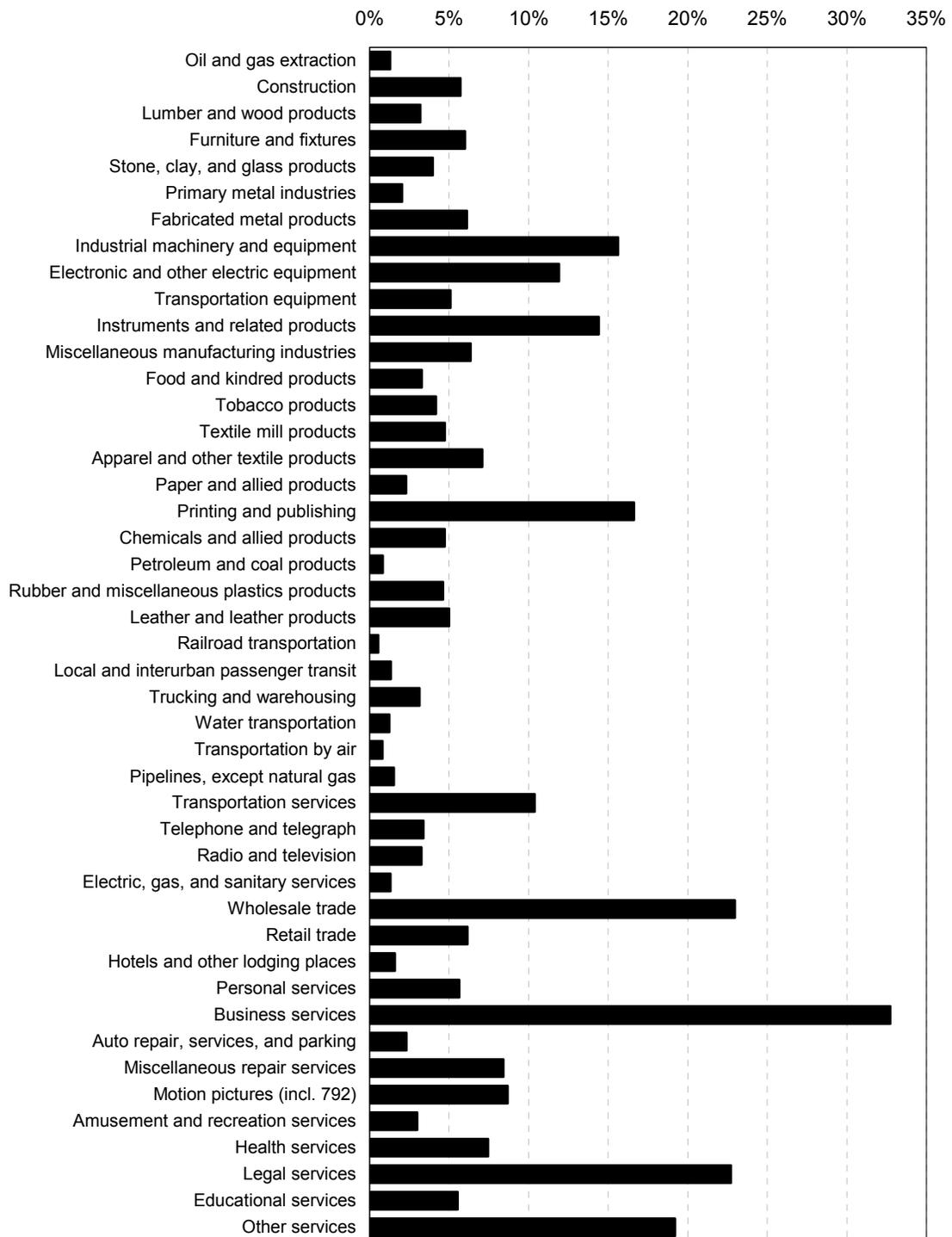


Figure 4. Time Evolution of the cross-industry Histogram of IT intensity
IT intensity is defined as the ratio of IT capital to total capital (the sum of IT and non-IT capital), all in 1994 real dollars. IT capital is defined as the sum of computers and software.

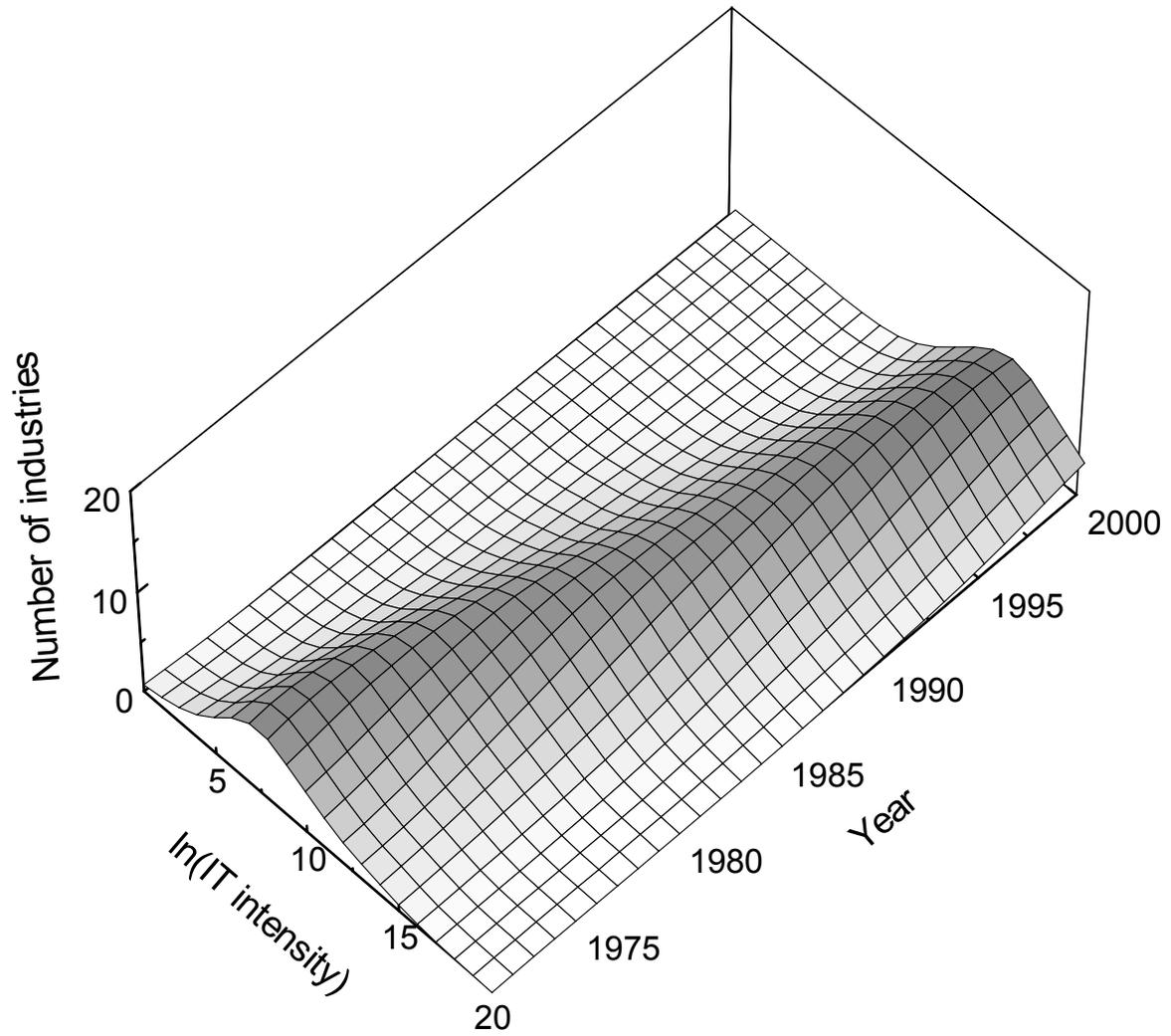
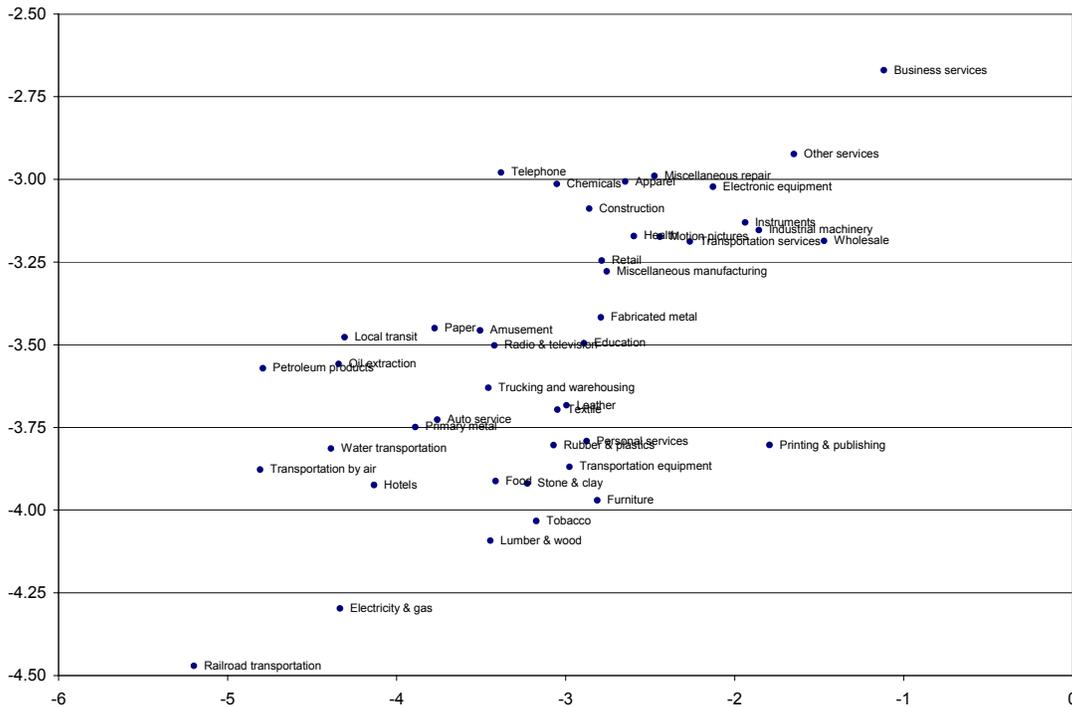


Figure 5. IT Intensity and Absolute Firm-Specific Variation in 2000

These graphs plot the logarithm of IT intensity against our absolute firm-specific variation 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 profit rate regressions, respectively. Dependent variables are absolute firm-specific variations ($\ln(\sigma_e^2)$) for stock returns, real sales growth rates, and profit rates. 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 variation measures are constructed using five-year rolling windows, we use a five-year average IT intensity. In constructing variation measures, firms with fewer than 30 monthly stock return observations and firms with fewer than 15 quarterly real sales growth or profit rate 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.

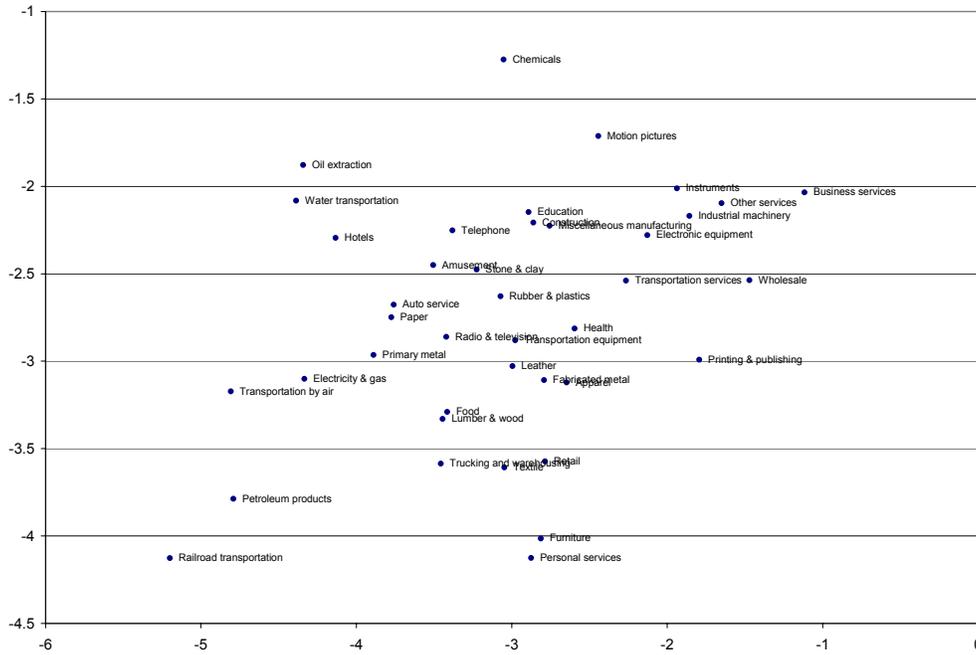
Panel A: IT intensity and absolute firm-specific variation of stock return in 2000

$$\ln(\sigma_{e, Stock}^2) = -2.472 + 0.273 \ln(IT) \quad t=4.003, \quad n = 43, \quad adj. R^2 = 0.390$$



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

$$\ln(\sigma_{Sales}^2) = -1.719 + 0.340 \ln(IT) \quad t = 3.243, n = 40, adj R^2 = 0.230,$$



Panel C: IT intensity and absolute firm-specific variation of profit rate in 2000

$$\ln(\sigma_{ROA}^2) = -2.668 + 1.168 \ln(IT) \quad t = 6.698, n = 40, adj R^2 = 0.559$$

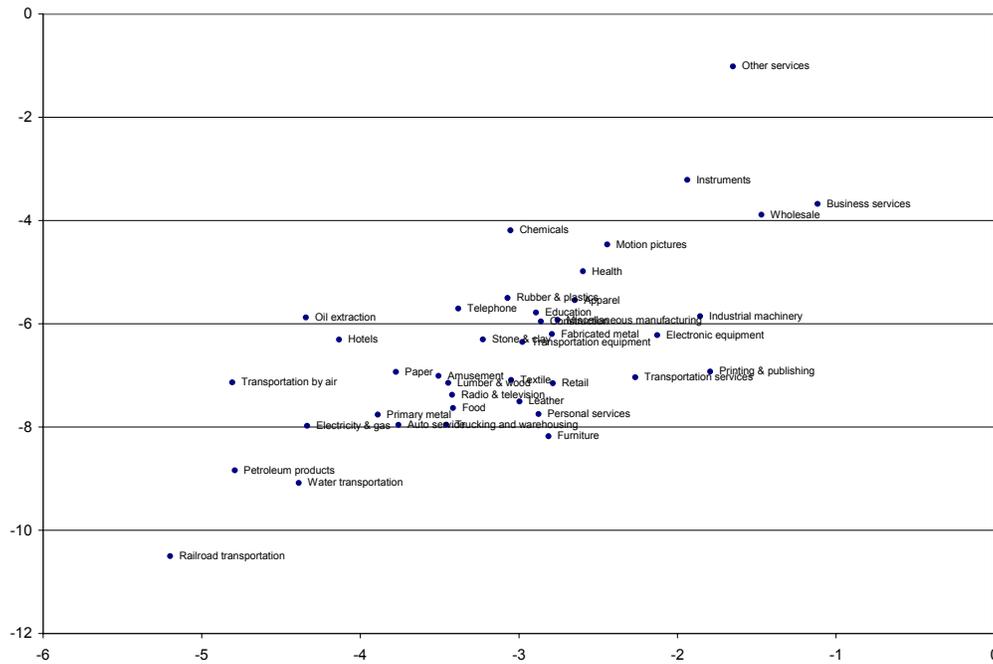


Table 1. Time-Series Patterns of Decomposed Variation Measures

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

Panel A: Ratios of firm-specific variation to systematic variation

		Stock Return	Sales Growth	profit rate
Whole (1971-2000)	Mean	6.04	4.86	7.10
	Median	4.58	3.16	3.27
	N	1431	1388	920
First Period (1971-1983) (1981-1983 for profit rate)	Mean	3.29	3.06	3.95
	Median	2.94	2.23	2.47
	N	609	566	128
Second Period (1984-2000)	Mean	8.08	6.10	7.61
	Median	6.63	3.90	3.38
	N	822	822	792

Sample is all industry-year observations

Panel B: Time series means and medians of industry cross-section correlations of firm-specific with systematic variation

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

Sample is all industry cross-section observations.

Table 2. Fama Macbeth Bivariate Regressions of Variation 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 variation measures based on stock returns, real sales growth rates, and profit rates, respectively. Dependent variables are absolute firm-specific ($\ln(\sigma_e^2)$), absolute systematic ($\ln(\sigma_m^2)$), and relative firm-specific ($\ln(\sigma_e^2) - \ln(\sigma_m^2)$) variations for stock returns, real sales growth rates, and profit rates. Systematic variation is firm-level variation 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 profitability. 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 variation measures are constructed using five-year rolling windows, we use the five-year average of IT intensity. In constructing variation measures, firms with fewer than 30 monthly stock return observations or fewer than 15 quarterly real sales growth or profitability 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		Variation Measure	Adj. R^2	No. of Industries	$\ln(IT)$ Estimate	Adj. <i>t</i> -stat
1971-2000	Stock	absolute firm-specific.	0.409	40.733	0.259^a	12.9
	Stock	absolute systematic.	0.215	40.733	0.156^a	7.20
	Stock	relative firm-specific.	0.246	40.733	0.102^a	7.25
	Sales	absolute firm-specific.	0.213	36.500	0.274^a	12.1
	Sales	absolute systematic.	0.133	36.500	0.233^a	6.56
	Sales	relative firm-specific.	0.030	36.500	0.040^c	1.79
1971-1983	Stock	absolute firm-specific.	0.477	39.769	0.268^a	16.7
	Stock	absolute systematic.	0.238	39.769	0.142^a	12.7
	Stock	relative firm-specific.	0.340	39.769	0.126^a	16.6
	Sales	absolute firm-specific.	0.226	32.538	0.280^a	24.6
	Sales	absolute systematic.	0.183	32.538	0.295^a	13.3
	Sales	relative firm-specific.	-0.009	32.538	-0.015	-0.766
1984-2000	Stock	absolute firm-specific.	0.357	41.471	0.251^a	8.16
	Stock	absolute systematic.	0.197	41.471	0.167^a	4.80
	Stock	relative firm-specific.	0.175	41.471	0.084^a	4.06
	Sales	absolute firm-specific.	0.204	39.529	0.269^a	6.96
	Sales	absolute systematic.	0.094	39.529	0.186^a	4.05
	Sales	relative firm-specific.	0.060	39.529	0.083^a	7.86
	profitability	absolute firm-specific.	0.319	36.647	0.751^a	7.65
	profitability	absolute systematic.	0.336	36.647	0.852^a	13.5
	profitability	relative firm-specific.	0.038	36.647	-0.101^b	-2.37

^a: Significant at 1 percent level.

^b: Significant at 5 percent level.

^c: Significant at 10 percent level.

Table 3. 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 variation 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.

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

Table 4. Fama-Macbeth Multivariate Regressions of Variations 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 variation measures based on stock returns, real sales growth rates, and profit rates, respectively. Dependent variables are absolute firm-specific ($\ln(\sigma_e^2)$), absolute systematic ($\ln(\sigma_m^2)$), and relative firm-specific ($\ln(\sigma_e^2) - \ln(\sigma_m^2)$) variations for stock returns, real sales growth rates, and profit rates. Systematic variation is firm-level variation related to market-wide and industry-wide events. In constructing variation 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 profit rate 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 variation 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	Variation Measure	Adj. R^2	No. of Inds.	$\ln(IT)$	$\ln(AGE)$	<i>I/K</i>	<i>BM</i>	$\ln(1+RD)$	$\ln(1+ADV)$	<i>HHI</i>	<i>DIS</i>	<i>LEV</i>	<i>LIQ</i>
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
	Prof. 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
	Prof. 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
Prof. 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 5. Fama-Macbeth Multivariate Regressions of Variations 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 variation measures based on stock returns, real sales growth rates, and profit rates, respectively. Dependent variables are absolute firm-specific ($\ln(\sigma_i^2)$), absolute systematic ($\ln(\sigma_m^2)$), and relative firm-specific ($\ln(\sigma_i^2) - \ln(\sigma_m^2)$) variations of stock returns, real sales growth rates, and profit rates. Systematic variation is firm-level variation related to market-wide and industry-wide events. In constructing variation 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 profit rate 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 variation 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.

Variation Measure	Adj. R^2	No. of Inds.	$\ln(IT)$	$\ln(AGE)$	<i>I/K</i>	<i>BM</i>	$\ln(1+RD)$	$\ln(1+ADV)$	<i>HHI</i>	<i>DIS</i>	<i>LEV</i>	<i>LIQ</i>	<i>FE</i>	<i>SEG</i>
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
Prof. 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
Prof. 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
Prof. 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 6. Fama-Macbeth Regressions of Change in Variation on IT

In this table, we test whether industries with high IT intensity exhibit faster subsequent variation growth. Dependent variables (ΔVOL) are five-year difference in each variation measure between year t and $t+5$. VOL is absolute firm-specific ($\ln(\sigma_e^2)$), absolute systematic ($\ln(\sigma_m^2)$), or relative firm-specific ($\ln(\sigma_e^2) - \ln(\sigma_m^2)$) variation in year t . Systematic variation is firm-level variation related to market-wide and industry-wide events. IT is IT intensity in year t for each industry. Since our variation 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 variation of stock returns, real sales growth rates, and profit rates, respectively. In constructing variation 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 profit rate 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	Variation	Measure	Adjusted R^2	No. of Industries	$\ln(IT)$ Estimate	Adj. t -stat	Variation 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
(profit rate) 1986-2000	Prof.	abs. firm.	0.221	37.333	0.424^a	15.333	-0.452^a	-8.108
	Prof.	abs. syst.	0.209	37.333	0.371^a	6.410	-0.374^a	-8.250
	Prof.	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.