Creative Destruction and Firm-Specific Performance Heterogeneity

Hyunbae Chun 1, Jung-Wook Kim 2, Randall Morck 3, and Bernard Yeung 4

Abstract

Firm-specific variation in stock returns, sales growth, and profit rates is elevated in recent decades in US industries that use information technology (IT) more intensively. We hypothesize that IT is associated with creative destruction, which mechanically widens the performance gap between winner and loser firms. Consistent with this, industries with elevated firm-specific variation post faster productivity growth. Our findings support endogenous growth theory models of Aghion and Howitt (1992, 1998), Aghion et al. (2004, 2005), and Acemoglu et al. (1997, 2003, 2005); and suggest that greater firm-specific performance variation in richer, faster growing countries with more transparent accounting, better financial systems, and more secure property rights might partly reflect more intensive creative destruction in those countries.

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

1 Assistant Professor of Economics, Queens College, City University of New York, Flushing, NY 11367. Tel: (718) 997-5450. Fax: (718) 997-5466. E-mail: hchun@qc1.qc.edu.
2 Assistant Professor of Finance, University of Alberta, Edmonton, Alberta, Canada T6G 2R6. Tel: (780) 492-7987. Fax: (780) 492-3325. E-mail: jungwook.kim@ualberta.ca.
3 Stephen A. Jarislowsky Distinguished Professor of Finance, University of Alberta, Edmonton, Alberta, Canada T6G 2R6. Tel: (780) 492-5683. Fax: (780) 492-3325. E-mail: randall.morck@ualberta.ca; Research Associate, National Bureau of Economic Research, 1050 Massachusetts Avenue, Cambridge, MA 02138.
4. Bernard Yeung. Abraham Krasnoff Professorship in Global Business Professor of Economics Professor of Management, Stern School of Management, New York University, New York NY 10002. Tel: (212) 998-0425. E-mail: byeung@stern.nyu.edu.

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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.”


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 widens the performance gap between winners and losers, elevating cross-sectional firm-specific performance variation in stock returns and fundamentals, hereinafter firm performance heterogeneity.

Consistent with this, using a panel of traditional US manufacturing and non-manufacturing industries from 1971 to 2000, we link more intensive use of IT to the elevated firm performance heterogeneity observed by Morck, Yeung, and Yu (2000), Campbell et al. (2001), Irvine and Pontiff (2004), Wei and Zhang (2004), and others. We also find enhanced total factor productivity (TFP) in these same industries, an expected consequence of intensified IT induced creative destruction.

We study traditional US manufacturing and non-manufacturing industries – like lumber and wood products, retail trade, and motion pictures – first because this avoids possible noise in dot.com stock returns; but more importantly because Bresnahan and Trajtenberg (1995), Helpman and Trajtenberg (1998), Jovanovic and Rousseau (2005), and others argue that IT is a general purpose technology (GPT) which, like electrification in the 1920s or steam power in the late 19th century, induces process and product innovation across most industries. Bresnahan and

Our results buttress certain models of economic growth, such as Pastor and Veronesi (2005), who model an economy absorbing a new technology and consequently exhibiting sustained elevated firm performance heterogeneity. Our findings also validate Aghion and Howitt (1992, 1998), Aghion et al. (2004, 2005), and Acemoglu et al. (1997, 2003, 2005), who formalize Schumpeter’s (1912) creative destruction.

Also, our findings clarify the economics underlying recent findings regarding firm performance heterogeneity. Pastor and Veronesi (2003) and Fama and French (2004) link heterogeneity to small or young firms. Philippon (2003), Gaspar and Massa (2004), and Irvine and Pontiff (2004) stress intensified price competition and deregulation. Morck et al. (2000), Fox et al. (2003), Bris et al. (2004), Durnev et al. (2004a), Huang (2004), Jin and Myers (2004), and Ozoguz (2004) link elevated firm performance heterogeneity to financial system development and transparency. Neatly tying these findings together, Schumpeter (1912) links creative destruction to intensified competition from new upstart firms that depend on external financing, Murphy et al. (1991) model regulation repressing creative destruction, and Schumpeter (1939) posits that intensified price competition trails waves of creative destruction. A significant relationship between IT and elevated firm performance heterogeneity survives controls for these factors and relevant industry characteristics, suggesting a robust overarching role for IT.

Finally, our results comfort financial economists like Roll (1988), who laments the low

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1 See also Bennett and Sias (2004), Brown and Kapadia (2004) and Fink et al. (2005) on corporate demography.
$R^2$ statistics of standard asset pricing models due to high cross sectional firm-specific variation in U.S. stock returns. Morck et al. (2000) find much better fits in countries with weak institutions. If the difference reflects faster creative destruction in countries with better institutions, there is no cause for lamentation. Rather, asset pricing models may find a new following among growth theorists, who might find the firm performance heterogeneity measures these models generate useful as indicators of the intensity of creative destruction.

The paper is structured as follows. Section 2 describes our IT intensity, firm performance heterogeneity, and TFP measures. Section 3 covers regressions and robustness checks. Section 4 concludes with a brief discussion of the implications of our results.

2. **Variables Construction**

This section describes our main variables and the data used to construct them. Our results are robust to various alternative constructions, described in detail in section 3.5.

2.2 **Information Technology Intensity**

*Bureau of Economic Analysis* (BEA) *Fixed Reproducible Tangible Wealth* (FRTW) data track investment in 61 asset classes from 1971 to 2000 by the two-digit industry of the investing firm. Because we are interested in IT as a GPT in traditional sectors, we drop industries whose primary products are IT goods or services: industrial machinery (SIC 35), which includes computer manufacturing, and business services(SIC 73), which includes computer related services and software. We also drop five financial industries (SIC codes in the 60s), whose

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2 King and Levine (1993) provide empirical validation for the dependence of these firms on external financing. Fogel et al. (2005) empirically link creative destruction to new firms.
accounting data are incomparable, and five agriculture and mining industries, whose IT investment is missing for part of the sample period. This leaves a 1,290 industry-year panel of IT investment spanning 30 years and 43 industries, 19 in manufacturing.

Stiroh (2002) and Brynjolfsson and Hitt (2003) link IT to TFP growth after the late 1980s, but Loveman (1994) and Stiroh (1998) find no link in earlier periods. Helpman and Trajtenberg (1998) explain this so-called IT productivity paradox – scant evidence of an IT impact on TFP in early studies – by showing that gains in productivity growth appear as IT diffuses across the economy and complementary inputs develop. Their solution is that accumulated IT, not contemporaneous IT spending, augments productivity. Given this, we an industry’s accumulated IT capital, not its IT investment rate, to capture creative destruction.

We convert flows into stocks with perpetual inventory models (Hall, 1990). Thus, industry i’s stock of asset k at time t is

\[ K_{i,k,t} = (1 - d_k)K_{i,k,t-1} + I_{i,k,t}, \]

with \( d_k \) an asset specific depreciation rate from Fraumeni (1997) and \( I_{i,k,t} \) the industry’s spending on type k assets that year. Asset prices are deflated with Törnqvist indexes as recommended by Jorgenson and Griliches (1967).

We define IT as 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). The IT depreciation rate is 0.31.

\(^3\) Herman (2000) describes FRTW. Our industries resemble Hobijn and Jovanovic (2001) and Stiroh (2002). Fama and French (1997) partition manufacturing more finely and non-manufacturing more coarsely, with 28 and 20
The *IT intensity* of industry $i$ in year $t$ is its stock of IT capital relative to other capital

$$IT_{i,t} = \frac{\sum_{k \in IT} K_{i,t,k}}{\sum_{k \in K} K_{i,t,k}}.$$  

for a 1,290 industry-year panel from 1971 to 200 spanning 43 industries, 19 in manufacturing.

The perpetual industry approach is, by construction, less accurate for earlier years. But a high depreciation rate and a probably genuine dearth of IT spending in the early 1970s mitigate this problem.

### 2.3 Firm Performance Heterogeneity

We now describe our firm performance metrics: stock returns, real sales growth and profit rate.

The *quarterly real sales growth rate* of firm $j$ in industry $i$ is

$$g_{j,i,t} = \frac{P_{i,t}^{-1} S_{j,i,t} - P_{i,t-1}^{-1} S_{j,i,t-1}}{\frac{1}{2} \left( P_{i,t}^{-1} S_{j,i,t} + P_{i,t-1}^{-1} S_{j,i,t-1} \right)}$$

where $S_{j,i,t}$ is nominal net sales by firm $j$ (Compustat quarterly item 2) during quarter $t$. Firm $j$ is assigned to industry $i$ based on Compustat industry codes. The price deflator $P_{i,t}$ is a BEA *Gross Product Originating* (GPO) two-digit industry gross output price index from 1977 on; or a *Bureau of Labor Statistics* (BLS) *Office of Employment Projection* gross output prices index for earlier years when GPO data are unavailable. We drop observations with Compustat footnotes, which flag unusual events – like mergers, accounting changes, and discontinued operations – that can render sales growth estimates problematic.
The profit rate of firm $j$ in industry $i$ during quarter $\tau$ is

$$\pi_{j,i,\tau} \equiv \frac{Y_{i,j,\tau}}{\frac{1}{2}(A_{j,i,\tau} + A_{j,i,\tau-1})}$$

with $A_{j,i,t}$ its total assets (quarterly item 44) at the end of quarter $t$ and $Y_{j,i,t}$ its operating income after depreciation. The last is operating income before depreciation (quarterly item 21) less depreciation and amortization (quarterly item 5). Again, we drop observations with footnotes.

Firm $i$’s stock return during month $t$ is $r_{j,i,t}$, its monthly total return from CRSP, which includes dividends and is adjusted for stock dividends, splits, and reverse splits.

To gauge the heterogeneity of each firm performance metrics within each industry, we remove common effects shared by all firms in an industry or 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 follow Durnev et al. (2004a) and regress

$$r_{j,t} = \alpha_{t,t} + \beta_{t,j,i} r_{m,j,t} + \beta_{i,j} r_{j,i,t} + \epsilon_{j,t},$$

with $t$ indexing the twelve monthly returns in year $t$. The value-weighted market and industry returns, $r_{m,t}$ and $r_{i,t}$, exclude firm $j$ to prevent spurious correlations with industry performance in industries with few firms.

Sales growth and profit rate regressions are identical to [5], but $t$ indexes quarterly performance over the twelve quarters up to and including those in year $t$. Analogs to $r_{m,t}$ and $r_{i,t}$ are sales weighted in sales growth regressions and asset-weighted in profit rate regressions.
The sum of squared residuals, $SSR_{i,j,t}$, and model variation, $SSM_{i,j,t}$, from running [5] on the $n_{j,t}$ observations for firm $j$ and year $t$ aggregate to the mean firm-specific variation

\[ \sigma^2_{e,j,t} = \frac{\sum_{j,t} SSE_{j,t}}{\sum_{j,t} n_{j,t}} \]

and mean systematic variation,

\[ \sigma^2_{s,j,t} = \frac{\sum_{j,t} SSM_{j,t}}{\sum_{j,t} n_{j,t}} \]

of industry $i$ for year $t$. Except in the robustness tests in §3.4, $n_{j,t} = 12$ for all firms. Firms with missing data are dropped. We require at least 5 firms in an industry. Since stock returns data are most complete and income data contains the most gaps, we have a more complete industry-year panel of stock returns heterogeneity and a substantially smaller panel of income heterogeneity measures. Sales growth heterogeneity is nearly as complete as stock returns, though fewer firms are used for some industry-year estimates.

An analog to the $R^2$ of [5] measures systematic over total variation, $\sigma^2_{e,j,t} + \sigma^2_{s,j,t}$, as

\[ R^2_{j,t} = \frac{\sigma^2_{s,j,t}}{\sigma^2_{e,j,t} + \sigma^2_{s,j,t}}. \]

These measures of sales growth and stock return heterogeneity exist for years $t \in [1971,$
2000], but are only available for profit rates for \( t \in [1981, 2000] \) because quarterly assets disclosure was not mandated until the late 1970s, making prior data sporadic and unrepresentative. Intersecting these data with those for IT intensity yields samples of 1,180 industry-years for stock return heterogeneity regressions on IT intensity, 1,010 for sales growth heterogeneity regressions, and only 611 for profit rate heterogeneity regressions.

### 2.3 Total Factor Productivity

Schumpeter (1912) argues that creative destruction enhances economic efficiency. To measure economic efficiency, we estimate each industry’s total factor productivity (TFP) as value added less labor and capital costs. We use annual, rather than quarterly data because the estimation technique requires data only disclosed annually.

Industry TFP growth is the change in logs of the industry’s TFP level. The logarithm of industry \( i \)'s TFP level in year \( t \) is

\[
\ln(TFP_{i,t}) = \sum_{j=1}^{J_{i,t}} \mu_{j,i,t} \left[ \ln(V_{j,i,t}) - \gamma_{L,j,i,t} \ln(L_{j,i,t}) - \gamma_{K,j,i,t} \ln(K_{j,i,t}) \right],
\]

where \( V_{j,i,t} \) is real value added by firm \( j \) in industry \( i \), \( \gamma_{L,j,i,t} \) and \( \gamma_{K,j,i,t} \) are the firm’s labor and capital cost shares, and \( L_{j,i,t} \) and \( K_{j,i,t} \) are its labor force and capital. Because the TFP literature stresses careful asset price indexes, we build industry TFP from firm data to use firm-level capital deflators.

Value-added, \( V_{j,i,t} \), is operating income before depreciation (Compustat item 13) plus labor and related expenses (item 42), all deflated by industry \( i \)'s two-digit GPO value-added deflator, as in Brynjolfsson and Hitt (2003). Prior to 1977, these deflators are unavailable, so we
use gross output and intermediate input prices from BLS Non-manufacturing Sector Multifactor Productivity data to construct our own. If labor and related expenses are unreported, we estimate them as industry average wage, from GPO data, times the firm’s workforce (item 29). If employees’ benefits are excluded from labor and related expenses (Compustat footnote 22), we estimate them from GPO industry benefits to total compensation ratio data.

The weights $\mu_{j,i,t}$ are firm j’s value added over its total industry’s value added in year $t$.

Labor force, $L_{j,i,t}$, is employees (item 29) and labor cost share, $\zeta_{j,i,t}$, is the average in years $t$ and $t-1$ of labor and related expenses (item 42 or the estimate described above) divided by this plus capital services costs.

Capital services costs are capital assets, defined below, times industry annual rental price of capital. As in Hall and Jorgenson (1967) and BLS (1997), the rental price of capital for asset $k$ in industry $i$ at time $t$ is

$$[10] \quad W_{k,i,t} = \frac{1 - \zeta_{k,t} - u_t z_{k,t}}{1 - u_t} \left( r_{j,t} + d_k - G_{k,t} \right) q_{k,t}$$

with $\zeta_{k,t}$ the investment tax credit, $u_t$ the corporate income tax rate, $z_{k,t}$ the present value of capital consumption allowances, $r_{j,t}$ the nominal internal rate of return, $d_k$ the depreciation rate, $G_{k,t}$ the asset-specific capital gain, and $q_{k,t}$ an investment deflator.\(^4\) Tax variables are from the BLS. Using FRTW data on the asset composition of each industry each year, we aggregate asset rental prices using the Törnqvist method to obtain industry rental prices of capital.

Real capital stock, $K_{j,i,t}$, is its book net property, plant and equipment (PP&E) (item 8) deflated, as in Hall (1990), to reflect the average age of these assets. Asset age is approximated
as balance sheet depreciation (items 7 minus 8) over income statement *depreciation and amortization* (item 14). Outliers are removed by taking a five year moving average and defining the age of firm $j$’s assets at time $t$, $a_{j,t}$, as this or 20 years, whichever is less. Taking all firm $j$’s assets as $a_{j,t}$ years old, we deflate their book PP&E with the FRTW industry deflator to estimate its *real capital stock*, $K_{j,i,t}$. Firm $j$’s *capital cost share*, $\kappa_{j,i,t}$, is then one minus $\kappa_{t,i}$. 

### 2.4 General Patterns in the Data

Figure 1 shows *IT intensity* broadly distributed and steadily rising across US industries, consistent with a GPT. 5 By the 1990s, IT is intensively used in such traditional manufacturing and non-manufacturing industries as printing, apparel, wholesales, retails, motion pictures, and health services. In contrast, R&D (not shown) is highly concentrated in the largest firms in a few technology industries, notably pharmaceuticals. 6 The introductory quote describing “*A wave of innovation across a broad range of technologies*” seems an apt portrayal of IT as a GPT.

[Figures 2, 3, and 4 about here]

Figure 2 graphs this variance decomposition, with column heights representing average total variation across all industries for a given year and their coloring breaking this into industry average *firm-specific variation* (white) and *systematic variation* (black), from [6] and [7]

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4 See Jorgenson (2001) for a discussion of the importance of capital input prices in the study of IT.

5 Corroborating this, managers of about 2,000 firms spanning a broad cross section of U.S. industries (National Science Foundation, 2004) report IT both lowering costs and raising quality. A 1997 survey of Fortune 500 IT managers links IT to improved and differentiated products (by improving customer service, targeting new customers, improving quality, and improving timeliness) and innovation (reducing total costs). Mukhopadhyay et al. (1997) report that IT in the US Post Office mainly speeds up mail processing; and Athey and Stern (2002) report that IT also speeds up emergency response systems.

6 See §4.3 and 4.4 below.
respectively. The $R^2_{ij}$ measure, [8], is the black section as a fraction of the total height of the column, and is graphed separately against time in Figure 3. Firm-specific variation in all three performance metrics rises substantially both in absolute magnitude and relative to systematic variation. Figure 4 shows that this surge affects a broad swath of industries.

This across-the-board upsurge in all three firm specific variation measures seconds the conclusion of Wei and Zhang (2004) – any explanation of rising firm specific variation in stock returns must also permit a contemporaneous rise in firm-specific fundamentals variation. Xu and Malkiel’s (2003) thesis of noise trading by increasingly important institutional investors cannot thus be a complete explanation. Nor can the Morck et al. (2000) suggestion of increasingly efficient firm-specific information capitalization. However, Bris et al. (2004), Durnev et al. (2004a, 2004b), Huang (2004), Jin and Myers (2004), Li et al. (2004), Ozoguz (2004), Fox et al. (2005), and others present evidence and theoretical arguments consistent with information capitalization and transparency being an important partial explanation.

These seemingly discordant findings are reconciled if rising firm-specific performance variation reflects intensified creative destruction, which is further invigorated by financial system development and enhanced transparency (Schumpeter, 1912; King and Levine, 1991).

This reconciliation seems promising, for the IT intensity industry ranks from Figure 1 correlate significantly with each of the three firm performance heterogeneity industry ranks from Figure 4. Figure 5 plots industry IT intensity against absolute firm specific variation in stock returns, real sales growth, and profit rate in the 1990s. A clear positive correlation is apparent in each panel, and is statistically significant at conventional levels.

[Figure 5 about here]
3. **Regressions**

To test the reconciliation, we regress firm performance heterogeneity on IT intensity. This section describes the regressions used to generate the tables. Their basic patterns of signs and significance are robust to a wide range of alternative variable constructions and econometric approaches, whose discussion is deferred to Section 3.5.

3.1 **Firm Performance Heterogeneity Dependent Variables**

To obtain near normal dependent variables, we take logs of [6] and [7]. Industry $i$’s year $t$ *absolute firm-specific variation* is $\ln(\sigma^2_{\varepsilon_{i,t}})$ and its *absolute systematic variation* is $\ln(\sigma^2_{m_{i,t}})$.

Since [8] is bounded by the unit interval and highly skewed, we apply a negative logistic transformation, as in Durnev *et al.* (2004a), to obtain *relative firm-specific variation*,

$$[11] \quad \psi_{i,t} \equiv \ln \left( \frac{1 - R^2_{i,t}}{R^2_{i,t}} \right) = \ln(\sigma^2_{\varepsilon_{i,t}}) - \ln(\sigma^2_{m_{i,t}}).$$

Table 1 displays summary statistics and correlations for our dependent variables.

[Table 1 about here]

3.2 **Performance Heterogeneity Bivariate Regressions**

We estimate industry clustered $t$-ratios from weighted least squares (WLS) fixed year effect regressions of the form

$$[12] \quad \ln(\sigma^2_{\varepsilon_{i,t}}) = b_0 + b_1 \ln(IT_{i,t-1}) + \sum_{s} \delta_s + u_{i,t}$$
or

\[ \psi_{t,i} = b_0 + b_1 \ln(IT_{t,i-1}) + \sum \delta_t + u_{t,i} \]

where the dependent variable is firm performance heterogeneity, \textit{absolute} or relative \textit{firm-specific variation} in returns, sales growth, or profit rates, and WLS weights are prior year-end industry market caps, real sales, or total assets, respectively.

WLS deprives small industries of undue influence. Equal weights would, for example, assign industries worth less than 5\% of the sample’s market cap a 40\% weight in determining regression coefficients.

Clustered standard errors are important because our annual performance variation measures for a given industry are virtually certain to be autocorrelated through time. Fixed year effects, \( d_t \), remove common time trends and macro-economic shocks, but our overlapping three-year windows for constructing fundamentals variation measures add to pre-existing autocorrelation within each time series of industry estimates. Our construction of \textit{IT intensity} using a perpetual inventory model also induces unavoidable autocorrelation in the time series of observations of that variable for each industry. This leaves point estimates are unbiased, but biases standard or Newey-West t-ratios upwards. Petersen (2005) shows that clustered standard errors adjust effectively for precisely this problem. Thus, the t-ratios shown are roughly an order of magnitude smaller than pooled panel t-ratios.

Since fundamentals variation reflects three year windows, \textit{IT intensity} is averaged across the same three years in those regressions. Stock returns regressions use annual \textit{IT intensity}. 
Panel A of Table 2 presents results from estimating [12] and [13]. IT intensity significantly explains all three measures of absolute firm-specific variation, but explains relative firm-specific variation for returns only.

Using $\psi_{i,t}$ in [13] is equivalent to putting absolute systematic variation on the right-hand side and constraining its coefficient to unity. This suggests a more general specification

$$\ln(\sigma^2_{e,i,t}) = b_0 + b_1 \ln(IT_{i,t-1}) + b_2 \ln(\sigma^2_{m,i,t}) + \sum_i \delta_i + u_{i,t}$$

Panel B shows IT intensity uniformly highly significant in these regressions.

3.3. Performance Heterogeneity Multiple Regressions

Although IT intensity and firm performance heterogeneity are significantly correlated in Table 2, omitted variables might induce spurious correlations. Thus, we turn to multivariate regressions.

Our main control variables proxy for industry characteristics, shown elsewhere to explain heterogeneity in one or another firm performance metric. These are:

Corporate Demography

Rising firm performance heterogeneity has been linked to a rising proportion of small or young firms (Campbell et al., 2001; Pastor and Veronesi, 2003; Fama and French, 2004; Bennett and Sias, 2005; Brown and Kapadia, 2005; and Fink et al., 2005). We therefore control for average firm age and size in each industry. Average firm age is years since first appearance in CRSP and
average firm size is the log of average market cap, real sales, or total assets in regressions explaining firm-specific variation in returns, sales growth, or profit rates, respectively.

The economics of why small or new firms should elevate performance heterogeneity are not fully understood. They may simply be more sensitive to small shocks (Philippon, 2003; Comin and Mulani, 2003; Gaspar and Massa, 2004; and Irvine and Pontiff, 2004). But Schumpeter (1914), Aghion and Howitt (1996), and others argues that new, initially small, firms carry the innovations that fuel creative destruction. Empirical work by King and Levine (1993), Fogel, Morck, and Yeung (2004), and others supports this view.

The former explanation justifies controls for corporate demography. But the latter holds an upsurge of new firms as a further sign of creative destruction, and cautions that the same controls might induce undesirable collinearity. Still, if IT remains significant, creative destruction remains plausible.

Competitive Pressure

Intense price competition is linked to elevated firm performance variation. We therefore control for industry Herfindahl-Hirschman indexes, based on annual firm sales from COMPUSTAT, and imports as a fraction of industry sales, annual NBER data from Feenstra, Romalis, and Schott (2002). Since imports are available only for manufacturing, we supplement it with a services sector indicator variable. This prevents imports from proxying for manufacturing.

Cutthroat price competition might magnify firm-specific shocks – turning minor setbacks into catastrophes and minor edges into lasting dominance (Philippon, 2003; Comin and Mulani, 2003; Gaspar and Massa, 2004; and Irvine and Pontiff, 2004). Consistent with this, monopoly (Gaspar and Massa, 2004), recent deregulation (Comin and Mulani, 2003; Irvine and
Pontiff, 2004), and trade liberalization (Irvine and Pontiff, 2004; but see Li et al. 2004) are associated with more heterogeneous firm performance.

A pure price competition story justifies controls, but creative destruction and price competition are interrelated. Schumpeter (1932) argues that creative destruction induces subsequent price competition, as a new technology is standardized. Thus, Brown and Goolsbee (2002) find internet sales reducing insurance premiums. Or, price competition might induce managers, desperate for any edge, to invest in innovation. Caves (1984) argues that foreign trade and investment often bring foreign ideas too. Indeed, Li et al. (2004) find elevated firm performance heterogeneity in countries open to global capital flows, more than trade. Any or all of these interactions might cause controls for price competition to impart undesirable biases. But if IT remains significant nonetheless, it is unlikely to be proxying for pure price competition.

**Research and Development**

IT is not the only investment that can lead to a technological edge. Romer (1986) and others focus on R&D. Moreover, Kothari et al. (2002) links R&D to future earnings variability; Chan et al. (2001) find similar results using stock returns; and Barron et al. (2002) link low R&D to dispersed analysts’ forecasts. We therefore control for research and development (R&D) intensity. R&D capital is constructed from R&D spending (Compustat item 46) using a precise analog to [1], substituting a 20% depreciation rate and the GDP deflator, as in Chan et al. (2001). R&D intensity is then an industry’s capitalized R&D over its total assets.

We control for R&D because it might be both correlated to IT intensity and an alternative font of creative destruction. However, inspection of our variable shows R&D capital highly
concentrated in a few industries and, within those, in the largest firms.\(^7\) R&D thus seems an unlikely cause of an economy-wide firm performance heterogeneity upsurge.

**Corporate Finance**

A firm’s leverage and liquidity might affect its firm-specific performance variation. Higher leverage, *ceteris paribus*, mechanically raises profits and stock returns volatility, though not necessarily that of sales growth. Cash reserves let firms weather ill times without sacrificing key assets (Myers and Majluf, 1984). Failing to control for these effects might induce noise – additional firm heterogeneity unrelated to IT intensity. We therefore include *liquidity* – industry current assets over current liabilities (Compustat annual items 4 over 5) – and *leverage* – industry short and long term debt over assets (annual items 9 plus 34 over 6).

All of this takes liquidity and leverage as exogenous, but these are set by the same managers who set IT investment. If high debt capacity permits more externally financed IT, or low liquidity signals access to external funds, controls for leverage and liquidity might bias the IT coefficients. However, if they are unaffected, a role for creative destruction is more plausible.

Section 3.5, on robustness, describes variants of the above controls as well as a substantial list of other controls variables – firm size distribution, exports, advertising capital, book to market ratios, capital investment, industrial diversification, geographical diversification, and others. Our findings are robust to all these alternatives.

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\(^7\) Others find a similar concentration. In 2000, R&D spending by the *industrial machinery, transportation equipment*, and *chemical products* industries accounted for almost 80% of total R&D spending in the manufacturing sector (NSF, 2003). A *National Science Foundation* survey (1999) reports 19 of the 20 firms with R&D spending above one billion dollars reside in four manufacturing industries – IBM and Hewlett-Packard are in *industrial machinery*; GE, Lucent, and Intel in *electric and electronic equipment*; GM and Ford in *transportation equipment*, and Johnson & Johnson and Pfizer in *chemical products*. Currently, Compustat classifies IBM as a *business services* firm because its sales of software and computer related services exceed its sales of computers.
Table 3 correlates our main control variables with performance heterogeneity and IT intensity (Panel A), and with each other (Panel B). The signs correspond to the interpretations above, but significance levels are sporadic — and these are pooled panel p-levels, which are biased upwards and so overstate the significance of the correlations (Petersen, 2005).

As in the bivariate regressions, we consider three specifications: absolute firm-specific performance variation as dependent variable (Table 4),

\[ \ln(\sigma_{\epsilon_i,t}^2) = b_0 + b_1 \ln(IT_{i,t-1}) + c \cdot x + \sum \delta_i + u_{i,t}, \]

relative firm-specific variation as the dependent variable (Table 5),

\[ \psi_{i,t} = b_0 + b_1 \ln(IT_{i,t-1}) + c \cdot x + \sum \delta_i + u_{i,t}, \]

and absolute firm-specific variation on the left-hand side, augmented by absolute systematic variation on the right-hand side (Table 6),

\[ \ln(\sigma_{\epsilon_i,t}^2) = b_0 + b_1 \ln(IT_{i,t-1}) + b_3 \ln(\sigma_{\sigma_{i,t}}^2) + c \cdot x + \sum \delta_i + u_{i,t} \]

with variables defined as in the bivariate regressions [12], [13] and [14] plus the matrix of controls x and coefficients vector c.
All three tables show *IT intensity* significantly correlated with absolute firm-specific variation in stock returns, sales growth and profitability throughout, regardless of the controls included. *IT intensity* correlates significantly with relative firm-specific variation of stock returns in all specifications, with that of sales growth in some (and bordering on statistical significance in the others), but not with that of profitability. The significance of *IT intensity* throughout Table 6 suggests that these problematic results for profitability in Table 5 imply an overly restrictive specification, rather than a genuine economic insignificance. Also, the profit heterogeneity regressions are run on a smaller sample, and so generate less precise parameters.

This exception explained, *IT intensity* coefficients are highly stable across specifications. In contrast, the controls’ coefficients are quite temperamental, with easily changing signs and significance levels. This suggests that IT is the underlying factor most consistently associated with elevated firm performance heterogeneity, and that the explanations associated with the various controls reflect aspects of this deeper explanation.

*Firm age* is typically negatively correlated with absolute firm specific performance variation, but *firm size* comes in only sporadically in explaining relative performance heterogeneity. This suggests that any firm demographics effect on firm-specific performance variation is largely subsumed by *IT intensity*. Any remaining demographic effect might reflect creative destruction not associated with IT, or an independent effect.

Competition controls are largely insignificant, suggesting that competition in the US during this period widens firm-specific firm performance variation only if it reflects IT induced creative destruction.
R&D is sporadically significant, and attains its strongest voice in explaining firm-specific profit rate variation – where IT intensity is least impressive. A correlation between abnormally high earnings and R&D is consistent with Schumpeter (1954), who argues that some forms of innovation are only possible for large, quasi-monopolistic firms with abundant internal funds. We relegate investigation of this to future research. Regardless, R&D intensity does not detract from IT in explaining elevated firm performance heterogeneity in the US in recent decades.

3.4 Productivity Regressions

If firm performance heterogeneity signals creative destruction, it should also presage TFP growth. IT is empirically linked to TFP growth, and we have linked firm performance heterogeneity to IT intensity as well. Testing for a direct link between TFP growth and firm performance heterogeneity appears something of an afterthought. However, if IT accelerates TFP growth by fuelling creative destruction, including firm performance heterogeneity should greatly diminish the coefficient and significance of IT in regressions explaining TFP growth.

Because Schumpeter (1912) links creative destruction only to medium long term growth, we measure industry TFP growth over 5 year intervals, and to avoid effects due to annual fluctuations, our dependent variable is the average of five such observations. Thus,

$$ TFPg_{i,t} = \frac{1}{5} \sum_{s=-4}^{s=0} \ln(TFP_{i,s}) - \ln(TFP_{i,s-5}) $$

with $TFP_{i,t}$ industry i TFP in year t, from [9].

We focus on firm-specific variation in stock returns to represent creative destruction because it is based on the most firm-level observations at the greatest frequency. We use non-
overlapping 5-year window, generating 234 industry-time observations, for our regressions

\[
TFP_{i,t} = c_0 + c_1 \text{av}[\ln(\sigma^2_{\varepsilon_{i,t-5}})] + c_2 \text{av}[\ln(TFP_{i,t-5})] + \sum_t \delta_t + \omega_{i,t}
\]

or

\[
TFP_{i,t} = c_0 + c \overline{\psi}_{i,t-5} + c_2 \text{av}[\ln(TFP_{i,t-5})] + \sum_t \delta_t + \omega_{i,t}.
\]

where \(\text{av}[\ln(\sigma^2_{\varepsilon_{i,t-5}})]\) and \(\overline{\psi}_{i,t-5}\) are the averages of the industry’s absolute and relative firm-specific stock return variation, \(\ln(\sigma^2_{\varepsilon_{i,t,s}})\) and \(\psi_{i,s}\), for \(s \in [t - 9, \ldots, t - 5]\); and \(\text{av}[\ln(TFP_{i,t-5})]\) is the average of the logarithm of its \(TFP\) level over the same years.

Table 7 reports regression results. We show regressions with and without lagged \(TFP\) level as a control. Including lagged levels in this type of panel regression might cause that variable to be correlated with the error term because increased TFP growth in one period raises the TFP level in the next. In output growth regressions, diminishing returns necessitate controlling for levels. However, Bernard and Jones (1996) argue that TFP growth ought not to display diminishing returns in general, and that controlling for initial levels is therefore unnecessary.

The table clearly shows that industries with higher firm-specific stock return variation post significantly faster TFP growth. The results are unaffected by the inclusion or exclusion of the previous period’s TFP level. They also pass a battery of robustness tests, described below.

### 3.5 Robustness Checks

This section considers alternative variable constructions, econometric approaches, and regression
specifications. These leave our results qualitatively unaffected; that is, that the pattern of rough coefficient magnitudes, signs and significance levels for IT intensity is preserved. Most of these robustness checks pertain to our results linking IT intensity to firm specific performance variation. Robustness results regarding our TFP regressions are at the end of the section.

**Alternative Variable Construction**

We consider several alternatives to our construction of IT intensity. In capitalizing IT investment, we use a perpetual inventory model [1] with a depreciation rate of 31% (Fraumeni, 1997). We use Törnqvist indexes to deflate IT capital. Alternative indexes have no qualitative effect, nor does making no adjustment for inflation at all.

We also experiment with alternative approaches to measuring firm performance heterogeneity in several ways.

To estimate sales growth and profit rate heterogeneity, we use overlapping three year rolling window. Our results are qualitatively insensitive to using five year overlapping windows instead. Using three year non-overlapping windows (i.e. dropping two out of every three years in our panel) still generates statistically significant coefficients on IT intensity as in the tables. For consistency we also estimated stock return variation using overlapping three and five year windows, and again the results are qualitatively unchanged.

We require complete data for a firm to be included in estimating firm performance heterogeneity for its industry. Repeating our tests using various inclusion thresholds (i.e. one, two, or three missing observations) generates qualitatively similar results to those in the tables.

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 in the tables.

We drop firm-quarter observations with Compustat footnotes. Retaining them changes nothing qualitatively.

We scale sales growth by the average of current and lagged sales in [3], and profits by the average of current and past total assets in [4]. Using last period’s sales or assets as the denominator leaves the results qualitatively unaffected.

We use value weighting of the industry and market indexes in [5], but using equal weighting does not qualitatively affect our results.


We gauge firm age by the number of years of CRSP data. This underestimates the ages of firms with early NASDAQ listings, listings on regional or foreign exchanges, and prior histories as unlisted firms. An alternative estimate of firm age (Hall, 1990) divides balance sheet depreciation by income statement depreciation (COMPUSTAT annual items 7 less 8 all over 14) to obtain a rough estimate of the age of the firm’s depreciable assets. This measure is highly positively correlated with years in CRSP ($r = 0.49$, $p << .01$) and substituting it into our regressions leaves our results qualitatively unchanged.

Our Herfindahl indexes are based on sales. Asset-based Herfindahls generate qualitatively similar results.

We capitalize R&D spending in our R&D control variable. Using simple current or lagged R&D spending over assets generates qualitatively similar results.
**Alternative Econometric Approaches**

We run WLS regressions, weighting observations by industry size the previous year. Since industry size might be endogenous, we rerun everything using 1970 weights for all years. No qualitative changes ensue.

We also run equally-weighted regressions. These generate qualitatively similar results throughout for stock return heterogeneity. The results for fundamentals heterogeneity are qualitatively unchanged if we drop industries with market capitalizations below 0.5% of the sample total.

Figure 5 presents scatter plots of $\ln(\sigma_i^2)$ for stock returns, sales growth, and profit rates against IT intensity. These show broad-based positive correlations, clearly not driven by outliers. More formally, winsorizing all variables at 1% generates qualitatively similar results.

An alternative to clustered standard errors, devised by Pontiff (1996), modifies Fama-MacBeth regressions by appending the method of Newey and West (1987). Fama-Macbeth regressions estimate panel coefficients as time-series averages of the coefficients of cross-section regression run separately for each year. IT intensity is significant in virtually all of these cross section regressions. Fama-MacBeth $t$-ratios are mean parameter estimates scaled by their observed standard deviation. To adjust for serial dependence and heteroskedasticity, Pontiff (1996) takes Newey-West $t$-ratios from regressions of the cross-section parameter estimates on a constant. Petersen (2005) shows that serial correlations to inflate $t$ statistics so generated. Still, the method is widely used and may have other advantages. Modified Fama-Macbeth regressions yield qualitatively similar results to those shown.

Our Herfindahl and import penetration variables are almost uniformly insignificant in the tables, but perform much better in modified Fama-MacBeth regressions, the econometric

All regressions in the tables include year fixed effects and industry clustered standard errors. Including fixed time and industry effects leaves the results qualitatively unchanged, except regressions of profit rate heterogeneity, in which \textit{IT intensity} becomes insignificant. We have a substantially shorter panel for profit rate heterogeneity regressions, so less robust results are understandable.

\textit{Alternative Regression Specifications}

We repeat our performance heterogeneity multiple regressions, supplemented with various additional controls. None change the results qualitatively.

We control average size of firm in each industry. As a robustness check, we also consider the distribution of firm size for each industry. Including the standard deviation of the logarithm of firm market capitalizations, sales, or total assets as a measure of firm-size dispersion yields qualitatively similar results to those shown.

IT and R&D are clearly not the only sources of innovation or creative destruction. Creative innovations might also arise from unique marketing strategies and any number of other sources. We therefore include as an additional control industry advertising expenses over property, plant, and equipment (PP&E) (Compustat item 45 over item 8). As a more general measure of intangible assets, we also include book to market ratios, industry total book value of equity over its corresponding market value (the industry total of annual item 60 over the sum of the products of 25 and 199). Including either or both of these variables does not qualitatively change our results.

The concentration of R&D and advertising in a few industries, mainly in the
managing 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.

Including institutional ownership is linked elsewhere (Xu and Malkiel, 2003; and Dennis and Strickland, 2004) to elevated firm-specific variation. We therefore include industry average institutional ownership from Gompers and Metrick (2001) as an additional control. Although this greatly shortens our panel, as institutional ownership is unavailable for early years, qualitatively similar findings nonetheless emerge.

Investment in conventional capital assets might also increase firm-level performance variation by increasing uncertainty about firms’ future cash flows. We therefore control for non-IT capital investment by including industry aggregate non-IT investment over industry aggregate non-IT capital, as defined in §2.2.

Firms with operations in many industries, all else equal, track the market more closely and their primary industry index less closely. Depending on which effect is greater, this might systematically raise or lower their firm-specific performance variation relative to that of pure-play firms. Also, Agarwal et al. (2004) argue that diversification raises investor uncertainty and increases stock return variation; and Morck et al. (1989) argue that investors view diversification per se as evidence of firm-specific governance problems. We therefore control for diversification with the number of two digit industries for which firms report positive sales, averaged for each industry each year. These data, from Compustat industry segment files, are available from 1985 on, but change format drastically in December 1998, when SFAS 131 superseded FASB 14. We thus have comparable data for this variable only from 1985 through 1998. Despite the reduced panel, including this control does not qualitatively affect our IT intensity results.
Multinational firms are subject to shocks, like currency fluctuations and foreign demand shocks, that barely affect purely domestic firms. But foreign sales can also dampen domestic shocks. We control for foreign exposure using industry foreign sales over total sales, from Compustat. Including this control leaves our results qualitatively unchanged.

**Productivity Regressions**

Using ten-year, rather than five-year intervals in our TFP growth regressions yields qualitatively similar results. Since industry size might be endogenous in our WLS regressions, we rerun everything using 1970 weights for all years. No qualitative changes ensue. We also run our absolute firm-specific variation regressions with absolute systematic variation as an added control. The results for for absolute firm-specific variation are qualitatively unchanged, and absolute systematic variation is uniformly insignificant.

In analogous regressions substituting firm-specific variation in sales growth or profit rates, these performance heterogeneity measures are insignificant. One possible explanation might be the forward looking nature of stock returns. Winners in creative destruction might see gently rising future sales and profits that, when capitalized by the market, drastically raise the share price. The same would be true of losers, for drastic share price drops might capitalize the expected results of more gradually declining sales and profits. Because firm-specific stock return variation is arguably the most sensitive of our firm performance heterogeneity measures, its greater explanatory power in *TFP growth* regressions is thus unsurprising.

The regression results in Table 7 are qualitatively unchanged if we include industry fixed effects as well as time fixed effects.

Adding R&D as an additional control in Table 7 also yields qualitatively unchanged
results.

Equally weighted regressions generate results qualitatively similar to those shown for absolute firm-specific variation. However, relative firm-specific variation becomes notably weaker, and even insignificant in some regressions. This might indicate noisier TFP growth estimates for smaller industries, or that creative destruction is more important in larger industries. Since growth in larger industries is ostensibly most economically important, even the latter would imply that the economic significance of our results is unaffected.

4. Conclusions

Elevated firm performance heterogeneity – cross sectional firm-specific variation in individual firms’ stock returns, real sales growth, and profit rates – is associated with intensive investment in information technology (IT). These findings are robust to a wide range of specifications, control variables, and econometric approaches.

Our results support IT serving as a general purpose technology (GPT), inducing a wave of innovation across many industries. Some firms make good use of these opportunities, while others do not, widening a chasm between winner and loser firms. This firm performance heterogeneity is a readily observable measure of ongoing creative destruction, the process which Schumpeter (1912) argues sustains economic growth. Consistent with this, industries with elevated firm performance heterogeneity exhibit faster total factor productivity (TFP) growth.

This interpretation of firm-specific performance heterogeneity permits reinterpretation of several recent findings regarding firm-specific stock returns and fundamentals variation, viz. 1. 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.

2. **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. This supports Baumol (1991),
Murphy et al. (1992), Gans, Hsu, and Stern (2002), and others who argue that sound private
property rights are a precondition for creative destruction.

3. **Creative destruction is more intense if corporations are more transparent**

Morck et al. (2000), Bris et al. (2004), Durnev et al. (2004a), Fox (2003), Huang (2004), Jin and
Myers (2004), and Ozoguz (2004) all link corporate transparency to firm-specific variation. Our
findings suggest one possible underlying economic explanation: better accounting disclosure
and more generally transparent stock markets permit entrepreneurs to raise external funds to
invest in new technologies, like IT, by making capital cheaper.

4. **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).

5. **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 other argue that openness encourages technology transfer, so the effect Li et al. (2004) observe could partially reflect creative destruction associated with that new technology.

6. **Creative Destruction Need Not Be Macroeconomically Stabilizing**

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 elevated macroeconomic variation growing slower.\(^8\) The two results are not mutually exclusive because firm-specific variation

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\(^8\) Ramey and Ramey interpret their finding as consistent with decreased uncertainty spurring investment, as in Pindyck (1991).
variation cancels out in aggregate measures. This fallacy of composition in variation means that the elevated firm-specific variation associated with creative destruction can aggregate into low volatility macroeconomic growth.


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York, NY).


Figure 1. Cross-industry Distribution of IT Intensity in the 1970s, 1980s, and 1990s
Industries are sorted by the 1990s IT intensity. The figure includes 39 industries. 4 industries (Local and interurban passenger transit, Pipelines, except natural gas, Miscellaneous repair services, and Legal services) are also omitted from 43 industries because firm specific variations of stock returns in Figure 3 are defined due to small number of firms.
Figure 2. Firm Performance Total Variation and Decomposition
Mean (industry equal-weight) total variation in firm-level performance decomposed into mean systematic (related to industry and economy factors) and mean firm-specific variation. Estimates of sales growth and profitability use quarterly data from three year rolling windows ending in the year indicated on the horizontal axis.

Panel A. Stock Returns

Panel B. Real Sales Growth

Panel C. Profitability (Operating Income over Assets)
Figure 3. Systematic Variation in Firm Performance as Fraction of Total Variation
Average fraction across all industries each year of variation in stock returns, sales growth, and profit rates explained by market and industry factors.
Figure 4. Cross-industry distributions of firm-specific stock return variation in the 1970s, 1980s, and 1990s.
Industries are sorted by the 1990s firm-specific variation. H indicates industries with high IT intensities defined as top 33% (13 industries from Figure 1). M and L are medium and bottom 33%.

- Engineering, accounting, and research services (H)
- Telephone and telegraph (M)
- Amusement and recreation services (L)
- Construction (M)
- Health services (H)
- Electronic and other electric equipment (H)
- Motion pictures (H)
- Chemicals and allied products (M)
- Instruments and related products (H)
- Miscellaneous manufacturing industries (H)
- Wholesale trade (H)
- Apparel and other textile products (H)
- Retail trade (H)
- Educational services (M)
- Water transportation (L)
- Fabricated metal products (H)
- Rubber and miscellaneous plastics products (M)
- Oil and gas extraction (L)
- Transportation services (H)
- Hotels and other lodging places (L)
- Radio and television (L)
- Transportation by air (L)
- Auto repair, services, and parking (L)
- Paper and allied products (L)
- Lumber and wood products (M)
- Leather and leather products (M)
- Printing and publishing (H)
- Textile mill products (M)
- Food and kindred products (M)
- Personal services (M)
- Transportation equipment (M)
- Furniture and fixtures (H)
- Petroleum and coal products (L)
- Primary metal industries (L)
- Trucking and warehousing (L)
- Stone, clay, and glass products (M)
- Electric, gas, and sanitary services (L)
- Tobacco products (M)
- Railroad transportation (L)

Legend:
- Firm-specific variation in the 1970s
- Firm-specific variation in the 1980s
- Firm-specific variation in the 1990s
Figure 5. Firm-Specific Variation of Stock Return and IT Intensity

These graphs plot the logarithm of IT intensity (x-axis) against the decade average of absolute firm-specific variation measure (y-axis). The area of bubble indicates the industry market capitalization, industry sales, total assets for stock returns, real sales growth, and profitability, respectively.

Panel A. Stock Returns

Panel B. Real Sales Growth
Panel C. Profitability (Operating Income over Assets)

\[ \text{ln}(\text{IT intensity in the 1990s}) \]

\[ \text{ln}(\text{Firm-specific variation of profitability in the 1990s}) \]
Table 1. Industry Summary Statistics Firm-Specific Performance Variation and Information Technology Intensity

Firm-specific performance variation by year is residual variation in firm-level regressions of total stock return, real sales growth, or profit rate on market and industry averages (weighted) of those variables. Industry averages exclude the firm in question to avoid spurious correlation problems in small industries where one firm is a substantial part of the industry. Absolute firm-specific variation, $\ln(\sigma^2_r)$ and relative firm-specific variation, $\ln(\sigma^2_r) - \ln(\sigma^2_m)$, are estimated using 12 monthly observations of stock return for each year. Real sales growth and profit rate variation measures are constructed using 12 quarterly observations over three-year overlapping rolling windows. We only include firms with 12 month observation in case of stock and 12 quarterly observations in case of real sales growth and profit rate. The sample period is 1971 to 2000 for stock return and real sales growth and 1981 to 2000 for profit rate. Sample is all firms in CRSP and COMPUSTAT in the 50 manufacturing and non-manufacturing (approximately 2-digit) industries excluding the finance sector (SIC 6000 to 6999). We exclude industries with fewer than 5 firms, or whose IT capital is not defined for each year. Two IT-producing industries are also excluded. IT capital is defined as the sum of computers and software. IT intensity is defined as the ratio of IT capital over non-IT capital.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>Firm Performance Heterogeneity</th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Deviation</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute firm-specific variation</td>
<td>Stock return</td>
<td>-4.279</td>
<td>-4.298</td>
<td>-6.520</td>
<td>-2.404</td>
<td>0.597</td>
<td>1180</td>
</tr>
<tr>
<td></td>
<td>Sales growth</td>
<td>-3.801</td>
<td>-3.824</td>
<td>-6.676</td>
<td>-1.232</td>
<td>0.986</td>
<td>1010</td>
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<tr>
<td></td>
<td>Profit rate</td>
<td>-7.592</td>
<td>-7.744</td>
<td>-11.387</td>
<td>-2.582</td>
<td>1.365</td>
<td>611</td>
</tr>
<tr>
<td>Relative firm-specific variation</td>
<td>Stock return</td>
<td>0.859</td>
<td>0.886</td>
<td>-1.025</td>
<td>3.122</td>
<td>0.528</td>
<td>1180</td>
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<td></td>
<td>Sales growth</td>
<td>0.697</td>
<td>0.707</td>
<td>-2.828</td>
<td>2.884</td>
<td>0.690</td>
<td>1010</td>
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<tr>
<td></td>
<td>Profit rate</td>
<td>0.867</td>
<td>0.876</td>
<td>-1.211</td>
<td>3.306</td>
<td>0.741</td>
<td>611</td>
</tr>
<tr>
<td>$\ln$(Information technology intensity)</td>
<td>-5.135</td>
<td>-5.010</td>
<td>-10.587</td>
<td>-0.590</td>
<td>1.829</td>
<td>1290</td>
<td></td>
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Panel B. Correlations of firm performance heterogeneity measures

<table>
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<tr>
<th>Stock Returns</th>
<th>Sales Growth</th>
<th>Profit Rate</th>
</tr>
</thead>
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<tr>
<td>Absolute</td>
<td>Relative</td>
<td>Absolute</td>
</tr>
<tr>
<td>Relative</td>
<td>Absolute</td>
<td>Relative</td>
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<table>
<thead>
<tr>
<th>Stock Returns</th>
<th>Absolute</th>
<th>Relative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative</td>
<td>0.406</td>
<td>(0.000)</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Sales Growth</th>
<th>Absolute</th>
<th>Relative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute</td>
<td>0.544</td>
<td>0.283</td>
</tr>
<tr>
<td>Relative</td>
<td>0.250</td>
<td>0.192</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Profit Rate</th>
<th>Absolute</th>
<th>Relative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute</td>
<td>0.436</td>
<td>0.146</td>
</tr>
<tr>
<td>Relative</td>
<td>-0.056</td>
<td>0.070</td>
</tr>
</tbody>
</table>

Numbers in parentheses are probability levels. Coefficients significant at 10% or better are in boldface.
Table 2. Panel Regressions of Firm-Specific Performance Heterogeneity on Information Technology Intensity with Time Fixed Effects and Industry Clustering

Dependent variables are absolute firm-specific variation, $\ln(\sigma^2_e)$ and relative firm-specific variation, $\ln(\sigma^2_e) - \ln(\sigma^2_m)$, for stock returns, sales growth, or profit rates. IT intensity, IT, is the ratio of IT capital (computers and software) to other capital. Weights are industry shares of market capitalization, sales, and total assets in regressions of stock returns, real sales growth rates, and profit rate, respectively. All t-statistics are adjusted for industry clustering to eliminate bias due to serial dependence within industries. IT intensity is lagged by one year. The sample period is 1971 to 2000 for stock return and real sales growth and 1981 to 2000 for profit rate. Stock return variation measures are estimated using 12 monthly observations each year. Real sales growth and profit rate variation measures are constructed using 12 quarterly observations over three-year overlapping rolling windows. In constructing variation measures, firms with fewer than 12 observations are excluded. The sample also excludes IT producing industries, the finance sector (SIC 6000 to 6999), industries with fewer than 5 firms, and industries whose IT capital is ill defined. Intercept estimates are not reported. Coefficients significant at 10% or better are in boldface.

Panel A. Absolute firm-specific variation with time fixed effects

<table>
<thead>
<tr>
<th>Dependent variable: Absolute firm-specific variation</th>
<th>Regression adjusted $R^2$</th>
<th>Sample size</th>
<th>Coefficient of $\ln(IT)$</th>
<th>Coefficient p-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock return</td>
<td>0.555</td>
<td>1,180</td>
<td>0.280</td>
<td>0.001</td>
</tr>
<tr>
<td>Sales growth</td>
<td>0.422</td>
<td>1,010</td>
<td>0.319</td>
<td>0.000</td>
</tr>
<tr>
<td>Profit rate</td>
<td>0.310</td>
<td>611</td>
<td>0.531</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Panel B. Absolute firm-specific variation with time fixed effects and controls for lagged systematic variation

<table>
<thead>
<tr>
<th>Dependent variable: Absolute firm-specific variation</th>
<th>Regression adjusted $R^2$</th>
<th>Sample size</th>
<th>Coefficient of $\ln(IT)$</th>
<th>Coefficient p-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock return</td>
<td>0.705</td>
<td>1,142</td>
<td>0.154</td>
<td>0.000</td>
</tr>
<tr>
<td>Sales growth</td>
<td>0.615</td>
<td>930</td>
<td>0.161</td>
<td>0.009</td>
</tr>
<tr>
<td>Profit rate</td>
<td>0.527</td>
<td>548</td>
<td>0.256</td>
<td>0.023</td>
</tr>
</tbody>
</table>

Panel C. Relative firm-specific variation with time fixed effects

<table>
<thead>
<tr>
<th>Dependent variable: Relative firm-specific variation</th>
<th>Regression adjusted $R^2$</th>
<th>Sample size</th>
<th>Coefficient of $\ln(IT)$</th>
<th>Coefficient p-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock return</td>
<td>0.617</td>
<td>1,180</td>
<td>0.077</td>
<td>0.000</td>
</tr>
<tr>
<td>Sales growth</td>
<td>0.426</td>
<td>1,010</td>
<td>0.060</td>
<td>0.161</td>
</tr>
<tr>
<td>Profit rate</td>
<td>0.116</td>
<td>611</td>
<td>-0.100</td>
<td>0.237</td>
</tr>
</tbody>
</table>
Table 3. Correlation Coefficients

Panel A. Correlations of firm performance heterogeneity and IT intensity with control variables

<table>
<thead>
<tr>
<th>Information Tech.</th>
<th>Stock Returns</th>
<th>Sales Growth</th>
<th>Profit Rate</th>
<th>IT intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(IT)</td>
<td>Absolute</td>
<td>Relative</td>
<td>Absolute</td>
<td>Relative</td>
</tr>
<tr>
<td></td>
<td>0.536</td>
<td>0.451</td>
<td>0.511</td>
<td>0.382</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Demography</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Age)</td>
<td>-0.369</td>
<td>-0.220</td>
<td>0.006</td>
<td>-0.232</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>ln(Size)</td>
<td>-0.017</td>
<td>0.183</td>
<td>0.115</td>
<td>-0.258</td>
</tr>
<tr>
<td></td>
<td>(0.566)</td>
<td>(0.000)</td>
<td>(0.867)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Competition</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herfindahl</td>
<td>-0.007</td>
<td>0.048</td>
<td>-0.040</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>(0.823)</td>
<td>(0.103)</td>
<td>(0.205)</td>
<td>(0.461)</td>
</tr>
<tr>
<td>Imports</td>
<td>0.111</td>
<td>0.104</td>
<td>0.133</td>
<td>0.128</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Services</td>
<td>0.118</td>
<td>0.006</td>
<td>0.015</td>
<td>0.017</td>
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<td>(0.000)</td>
<td>(0.829)</td>
<td>(0.638)</td>
<td>(0.600)</td>
</tr>
<tr>
<td>Technology</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(1+R&amp;D)</td>
<td>0.249</td>
<td>0.066</td>
<td>0.266</td>
<td>0.060</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.023)</td>
<td>(0.000)</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Financing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage</td>
<td>0.030</td>
<td>0.031</td>
<td>0.102</td>
<td>0.092</td>
</tr>
<tr>
<td></td>
<td>(0.305)</td>
<td>(0.285)</td>
<td>(0.205)</td>
<td>(0.461)</td>
</tr>
<tr>
<td>Liquidity</td>
<td>-0.058</td>
<td>-0.073</td>
<td>-0.102</td>
<td>-0.106</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.013)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
</tbody>
</table>

Numbers in parentheses are probability levels. Coefficients significant at 10% or better are in boldface.

Panel B. Correlations of control variables with each other

<table>
<thead>
<tr>
<th>Demography</th>
<th>Competition</th>
<th>Technology</th>
<th>Financing</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Age)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Size)</td>
<td>0.506</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Herfindahl</td>
<td>-0.428</td>
<td>-0.225</td>
<td>(0.000)</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Imports</td>
<td>0.183</td>
<td>0.022</td>
<td>-0.095</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.445)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Services</td>
<td>-0.445</td>
<td>-0.206</td>
<td>0.329</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>ln(1+R&amp;D)</td>
<td>-0.074</td>
<td>-0.038</td>
<td>0.230</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.176)</td>
<td>(0.138)</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.194</td>
<td>0.227</td>
<td>-0.173</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Liquidity</td>
<td>-0.037</td>
<td>0.061</td>
<td>0.307</td>
</tr>
<tr>
<td></td>
<td>(0.192)</td>
<td>(0.029)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Numbers in parentheses are probability levels. Coefficients significant at 10% or better are in boldface.
Table 4. Multivariate regressions of absolute firm-specific variation in firm-level performance within an industry on industry level information technology intensity and controls, including time fixed effects.

<table>
<thead>
<tr>
<th></th>
<th>Stock Return</th>
<th>Sales Growth Rate</th>
<th>Profit Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4a.1  4a.2  4a.3  4a.4  4a.5</td>
<td>4b.1  4b.2  4b.3  4b.4  4b.5</td>
<td>4c.1  4c.2  4c.3  4c.4  4c.5</td>
</tr>
<tr>
<td><strong>Information Technology</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(IT)</td>
<td>0.202  0.311  0.234  0.216  0.104</td>
<td>0.319  0.259  0.211  0.286  0.199</td>
<td>0.449  0.446  0.245  0.364  0.126</td>
</tr>
<tr>
<td></td>
<td>(0.002)  (0.000)  (0.006)  (0.000)  (0.001)</td>
<td>(0.000)  (0.000)  (0.004)  (0.000)  (0.032)</td>
<td>(0.000)  (0.000)  (0.090)  (0.007)  (0.423)</td>
</tr>
<tr>
<td><strong>Corporate Demography</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Age)</td>
<td>-0.747  -0.740  -0.045  -0.401  -0.172</td>
<td>-0.902</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)  (0.000)  (0.902)  (0.109)  (0.704)</td>
<td></td>
<td>(0.030)</td>
</tr>
<tr>
<td>ln(Size)</td>
<td>0.057  0.022  0.026  -0.118  -0.159  -0.050</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.254)  (0.471)  (0.782)  (0.272)  (0.364)  (0.754)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Competition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herfindahl</td>
<td>-0.107  0.227  0.508  -0.389  -4.940  -5.942</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.940)  (0.655)  (0.805)  (0.840)  (0.173)  (0.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imports</td>
<td>-0.038  -0.042  0.441  0.006  1.007  -0.927</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.947)  (0.845)  (0.541)  (0.994)  (0.627)  (0.695)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Services</td>
<td>0.153  0.134  -0.483  -0.426  -0.806</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.494)  (0.181)  (0.176)  (0.503)  (0.237)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Technology</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(1+R&amp;D)</td>
<td>0.554  0.165  1.693  0.635  3.383  2.987</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.142)  (0.596)  (0.001)  (0.300)  (0.014)  (0.061)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Financing</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.488  -2.006  -2.691  -2.480  -0.149  1.728</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.604)  (0.000)  (0.012)  (0.067)  (0.920)  (0.383)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.218  0.162  -0.091  -0.545  0.923  0.117</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.230)  (0.056)  (0.681)  (0.086)  (0.054)  (0.835)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.711  0.565  0.567  0.576  0.763  0.421  0.467  0.482  0.472  0.527  0.330  0.361  0.410  0.353  0.478</td>
<td>0.330  0.361  0.410  0.353  0.478</td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
<td>1180  1180  1180  1180  1180  1010  1010  1010  1010  1010  611  611  611  611  611</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Numbers in parentheses are probability levels. Coefficients significant at 10% or better are in boldface.
Table 5 Multivariate Regressions of absolute firm-specific variation on IT, controls, and lagged absolute systematic variation, including time fixed effects.

<table>
<thead>
<tr>
<th></th>
<th>Stock Return</th>
<th></th>
<th>Sales Growth Rate</th>
<th></th>
<th>Profit Rate</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5a.1</td>
<td>5a.2</td>
<td>5a.3</td>
<td>5a.4</td>
<td>5a.5</td>
<td>5b.1</td>
</tr>
<tr>
<td><strong>Information Technology</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(\text{IT})$</td>
<td>0.141</td>
<td>0.178</td>
<td>0.141</td>
<td>0.131</td>
<td>0.091</td>
<td>0.149</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.031)</td>
</tr>
<tr>
<td><strong>Corporate Demography</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(\text{Age})$</td>
<td>-0.488</td>
<td>-0.547</td>
<td>-0.115</td>
<td>-0.303</td>
<td>-0.213</td>
<td>-0.546</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.499)</td>
<td>(0.031)</td>
<td>(0.054)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>$\ln(\text{Size})$</td>
<td>0.032</td>
<td>0.016</td>
<td>0.018</td>
<td>-0.067</td>
<td>-0.010</td>
<td>0.039</td>
</tr>
<tr>
<td>(0.222)</td>
<td>(0.490)</td>
<td>(0.654)</td>
<td>(0.338)</td>
<td>(0.878)</td>
<td>(0.744)</td>
<td></td>
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<td><strong>Competition</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herfindahl</td>
<td>-0.111</td>
<td>0.211</td>
<td>-0.666</td>
<td>-1.304</td>
<td>-2.594</td>
<td>-3.469</td>
</tr>
<tr>
<td>(0.862)</td>
<td>(0.464)</td>
<td>(0.519)</td>
<td>(0.251)</td>
<td>(0.159)</td>
<td>(0.039)</td>
<td></td>
</tr>
<tr>
<td>Imports</td>
<td>-0.185</td>
<td>-0.122</td>
<td>0.322</td>
<td>0.048</td>
<td>0.474</td>
<td>-1.709</td>
</tr>
<tr>
<td>(0.522)</td>
<td>(0.513)</td>
<td>(0.456)</td>
<td>(0.930)</td>
<td>(0.713)</td>
<td>(0.352)</td>
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<tr>
<td>Services</td>
<td>0.074</td>
<td>0.085</td>
<td>-0.075</td>
<td>-0.255</td>
<td>-0.203</td>
<td>-0.417</td>
</tr>
<tr>
<td>(0.521)</td>
<td>(0.275)</td>
<td>(0.586)</td>
<td>(0.235)</td>
<td>(0.589)</td>
<td>(0.313)</td>
<td></td>
</tr>
<tr>
<td><strong>Technology</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(1+\text{R&amp;D})$</td>
<td>0.188</td>
<td>0.148</td>
<td>0.855</td>
<td>0.362</td>
<td>2.293</td>
<td>2.977</td>
</tr>
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<td>(0.448)</td>
<td>(0.536)</td>
<td>(0.004)</td>
<td>(0.411)</td>
<td>(0.001)</td>
<td>(0.020)</td>
<td></td>
</tr>
<tr>
<td><strong>Financing</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.010</td>
<td>-1.344</td>
<td>-1.143</td>
<td>-1.354</td>
<td>-0.615</td>
<td>1.060</td>
</tr>
<tr>
<td>(0.981)</td>
<td>(0.001)</td>
<td>(0.007)</td>
<td>(0.060)</td>
<td>(0.585)</td>
<td>(0.446)</td>
<td></td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.120</td>
<td>0.113</td>
<td>-0.120</td>
<td>-0.458</td>
<td>0.294</td>
<td>0.175</td>
</tr>
<tr>
<td>(0.253)</td>
<td>(0.088)</td>
<td>(0.293)</td>
<td>(0.028)</td>
<td>(0.262)</td>
<td>(0.728)</td>
<td></td>
</tr>
<tr>
<td><strong>Systematic Variation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Abs. systematic</td>
<td>0.419</td>
<td>0.625</td>
<td>0.622</td>
<td>0.618</td>
<td>0.310</td>
<td>0.537</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.757</td>
<td>0.709</td>
<td>0.706</td>
<td>0.709</td>
<td>0.778</td>
<td>0.616</td>
</tr>
<tr>
<td>Sample size</td>
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<td>1142</td>
<td>1142</td>
<td>1142</td>
<td>1142</td>
<td>930</td>
</tr>
</tbody>
</table>

Numbers in parentheses are p-levels for rejecting a zero coefficient. Coefficients significant at 10% or better are in boldface.
Table 6. Multivariate regressions of relative firm-specific variation in firm-level performance within an industry on industry level information technology intensity and controls, including time fixed effects.

<table>
<thead>
<tr>
<th>Stock Return</th>
<th>Sales Growth Rate</th>
<th>Profit Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>6a.1 6a.2 6a.3 6a.4 6a.5</td>
<td>6b.1 6b.2 6b.3 6b.4 6b.5</td>
<td>6c.1 6c.2 6c.3 6c.4 6c.5</td>
</tr>
<tr>
<td><strong>Information Technology</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(\text{IT})$</td>
<td>0.060 0.096 0.091 0.065 0.060</td>
<td>0.064 0.066 0.055 0.083 0.103</td>
</tr>
<tr>
<td>(0.008) (0.000) (0.000) (0.004)</td>
<td>(0.110) (0.109) (0.234) (0.076) (0.041)</td>
<td>-0.049 -0.142 -0.169 -0.055 -0.094</td>
</tr>
<tr>
<td><strong>Corporate Demography</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(\text{Age})$</td>
<td>-0.060 -0.069 0.056 0.123</td>
<td></td>
</tr>
<tr>
<td>(0.116) (0.206) (0.683) (0.320)</td>
<td>(0.000)</td>
<td>0.579 0.434</td>
</tr>
<tr>
<td>$\ln(\text{Size})$</td>
<td>-0.029 -0.045 -0.015 -0.062 -0.033 -0.034</td>
<td></td>
</tr>
<tr>
<td>(0.021) (0.013) (0.738) (0.079)</td>
<td>(0.610)</td>
<td>(0.534)</td>
</tr>
<tr>
<td><strong>Competition</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herfindahl</td>
<td>-0.069 0.098 -0.502 -0.738 -3.440 -0.908</td>
<td></td>
</tr>
<tr>
<td>(0.764) (0.594) (0.416) (0.255) (0.182) (0.535)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imports</td>
<td>-0.525 -0.489 0.228 0.025 2.145 0.944</td>
<td></td>
</tr>
<tr>
<td>(0.044) (0.045) (0.382) (0.940) (0.002) (0.168)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Services</td>
<td>-0.021 -0.087 0.079 0.045 0.162 -0.159</td>
<td></td>
</tr>
<tr>
<td>(0.696) (0.322) (0.272) (0.694) (0.444) (0.565)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Technology</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(1+\text{R&amp;D})$</td>
<td>-0.163 -0.152 0.077 0.092 0.811 0.826</td>
<td></td>
</tr>
<tr>
<td>(0.307) (0.306) (0.522) (0.739) (0.129) (0.137)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Financing</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage</td>
<td>0.305 -0.187 -0.081 -0.503 1.392 2.925</td>
<td></td>
</tr>
<tr>
<td>(0.119) (0.226) (0.831) (0.243) (0.234) (0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.098 0.017 -0.134 -0.252 -0.061 -0.198</td>
<td></td>
</tr>
<tr>
<td>(0.007) (0.748) (0.140) (0.046) (0.828) (0.503)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Adjusted R$^2$</strong></td>
<td>0.625 0.626 0.619 0.621 0.636 0.425 0.427 0.425 0.429 0.434 0.180 0.188 0.134 0.140 0.274</td>
<td></td>
</tr>
<tr>
<td><strong>Sample size</strong></td>
<td>1180 1180 1180 1180 1180 1010 1010 1010 1010 611 611 611 611 611</td>
<td></td>
</tr>
</tbody>
</table>

Numbers in parentheses are probability levels. Coefficients significant at 10% or better are in boldface.
Table 7. Regressions of firm-specific variation measure on TFP growth

Data are a panel of US industries followed from 1971 to 2000 in non-overlapping five year windows. The dependent variable is five-year TFP growth and the independent variable of interest is firm-specific variation in the stock returns of firms in that industry over that period. This is either the log of the absolute magnitude of this variation or the same less the log of systematic (market and industry-related) variation. A control for the industry’s TFP level at the beginning of the five year window is included in alternate regressions.

<table>
<thead>
<tr>
<th>Performance Heterogeneity</th>
<th>7.1</th>
<th>7.2</th>
<th>7.3</th>
<th>7.4</th>
<th>7.5</th>
<th>7.6</th>
<th>7.7</th>
<th>7.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute firm-specific stock</td>
<td>0.336</td>
<td>0.433</td>
<td></td>
<td></td>
<td>0.304</td>
<td>0.351</td>
<td></td>
<td></td>
</tr>
<tr>
<td>return variation: ln(σ_i^2)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative firm-specific stock</td>
<td>0.635</td>
<td>0.686</td>
<td></td>
<td></td>
<td>0.474</td>
<td>0.433</td>
<td></td>
<td></td>
</tr>
<tr>
<td>return variation: ln(σ_i^2) - ln(σ_m^2)</td>
<td>(0.081)</td>
<td>(0.049)</td>
<td></td>
<td></td>
<td>(0.117)</td>
<td>(0.076)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IT intensity</td>
<td>0.025</td>
<td>0.081</td>
<td>0.059</td>
<td>0.115</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial ln(TFP)</td>
<td>-0.106</td>
<td>-0.047</td>
<td>-0.137</td>
<td>-0.104</td>
<td>(0.018)</td>
<td>(0.102)</td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>0.418</td>
<td>0.464</td>
<td>0.370</td>
<td>0.379</td>
<td>0.418</td>
<td>0.483</td>
<td>0.383</td>
<td>0.420</td>
</tr>
<tr>
<td>Sample size</td>
<td>234</td>
<td>234</td>
<td>234</td>
<td>234</td>
<td>233</td>
<td>233</td>
<td>233</td>
<td>233</td>
</tr>
</tbody>
</table>

Numbers in parentheses are probability levels. Coefficients significant at 10% or better are in boldface.