Journal of Financial Economics 89 (2008) 109–135

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Creative destruction and firm-specific performance heterogeneity ☆

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ARTICLE INFO

Article history:
Received 27 July 2006
Received in revised form
19 March 2007
Accepted 15 June 2007
Available online 15 March 2008

JEL classification:
G12
G14
N22
O33

Keywords:
Creative destruction
Firm-specific variation
Information technology

ABSTRACT

Traditional U.S. industries with higher firm-specific stock return and fundamentals performance heterogeneity use information technology (IT) more intensively and post faster productivity growth in the late 20th century. We argue that this mechanically reflects a wave of Schumpeter's creative destruction disrupting a wide swath of industries, with successful IT adopters unpredictably undermining established firms. This validates endogenous growth theory models of creative destruction and suggests intensified creative destruction as explaining findings associating greater firm-specific performance variation with higher per capita GDPs, economy growth rates, accounting standards, financial system development, and property right protection.

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.

☆ An earlier version of this paper circulated as "Patterns of Comovement: The Role of Information Technology in the US Economy" and as NBER Working Paper No. 10937. This research was in progress when Randall Morck was a visiting professor at Harvard. Chun, Kim, and Morck acknowledge partial funding from PSC-CUNY, University of Alberta SAS and Nova fellowships, and the SSHRC, respectively. We thank Philippe Aghion, Cliff Ball, Nick Bollen, Aida Charoenrook, Wonseok Choi, Bill Christie, Art Durnev, Mara Faccio, Daniel Ferreira, Akiko Fujimoto, David Gabel, Amar Gande, Bruno Gerard, Luca Grilli, Campbell Harvey, Peter Howitt, Mark Huson, Boyan Jovanovic, Aditya Kaul, Chansog Kim, Jason Lee, Ross Levine, Kyung-Mook Lim, Ron Masulis, Vikas Mehrotra, Robert Shiller, James Stock, Hans Stoll, and seminar participants at the University of Alberta, Boston College, Boston University, Brown University, the Canadian Economic Association, Chinese University of Hong Kong, Copenhagen Business School, CUNY Graduate Center, the Corporate Governance and Capital Markets Conference in Lisbon, Duke University, Ewha Womans University, the European Finance Association, University of Florida, Georgetown University, Harvard University, Hong Kong Polytechnic, the International Industrial Organization Conference, the Korea Academic Society of Industrial Organization, Kyunghee University, University of Miami, New York University, Ohio State University, Queens College, Sogang University, Stockholm School of Economics, University of Toronto, Vanderbilt University, and the Western Economic Association. We are also most grateful to an anonymous referee for particularly helpful comments.
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doi:10.1016/j.jfineco.2007.06.005

1. Introduction

Elevated heterogeneity in firm-specific stock return and fundamentals performance is significantly correlated with more intensive use of information technology (IT) and faster productivity growth across a panel of traditional U.S. industries from 1971 to 2000. We argue that this suggests IT, at least in the early decades of its absorption into the economy in the late 20th century, induced a tremor of Schumpeter's (1912) *creative destruction* across a wide swath of U.S. industries. New innovators, with abnormally good performance, unpredictably and continually rose to dislodge established firms, abnormally depressing their performance. This suggests intensified creative destruction as a new explanation for the rising firm performance heterogeneity among publicly traded firms in recent decades in the U.S. and other developed economies observed by Morck, Yeung, and Yu (2000), Campbell, Lettau, Malkiel, and Xu (2001), Irvine and Pontiff (2004), Wei and Zhang (2006), and others.

We study publicly traded firms in traditional U.S. manufacturing and nonmanufacturing industries such as lumber and wood products, retail trade, and motion pictures, that is, we abstract from IT-related firms. We do so because this avoids possible noise in dot.com stock returns and, 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 electricity in the early 20th century or steam power early in the industrial revolution, induces process and product innovation across most industries. Bresnahan and Trajtenberg (1995) and Helpman and Trajtenberg (1998) model GPTs driving economic growth, and cite IT as an example. Oliner and Sichel (2000), Jorgenson (2001), Stiroh (2002), and Brynjolfsson and Hitt (2003) also link IT to economy-wide enhanced productivity.

Our findings complement approaches to economic growth theory, such as Pastor and Veronesi (2005), which model an economy absorbing a new technology and consequently exhibiting sustained elevated firm performance heterogeneity. More generally, this paper builds on Aghion and Howitt (1992, 1998), Aghion, Angeletos, Banerjee, and Manova (2004), Aghion, Howitt, and Mayer-Foulkes (2005), Acemoglu (2005), Acemoglu, Aghion, and Zilibotti (2006), and other formalizations of Schumpeter's (1912) concept of creative destruction.

Other research into rising firm-specific performance variation can readily be reinterpreted in light of our findings. Pastor and Veronesi (2003), Fama and French (2004), Fink, Fink, Grullon, and Weston (2005), Bennett and Sias (2006), and Brown and Kapadia (2007) link heterogeneity to small or young firms. Philippon (2003), Irvine and Pontiff (2004), and Gaspar and Massa (2006) stress intensified competition and deregulation. Morck, Yeung, and Yu (2000), Fox, Morck, Yeung, and Durnev (2003), Bris, Goetzmann, and Zhu (2004), Durnev, Li, Morck, and Yeung (2004), Huang (2004), Ozoguz (2004), Biddle and Hilary (2006), and Jin and Myers (2006) link elevated firm performance heterogeneity to financial system development and transparency. Neatly tying all these findings together, Schumpeter (1912) links creative destruction to intensified competition from new, initially small, upstart firms that need external financing to grow rapidly,[1] Murphy, Shleifer, and Vishny (1991) model regulation repressing creative destruction, and Schumpeter's (1939) theory of business cycles posits that intensified competition trails waves of creative destruction. The link we find between IT and elevated firm performance heterogeneity nonetheless survives controls for all these factors as well as for other relevant industry characteristics, suggesting a robust overarching role for IT.

Our results should comfort financial economists, like Roll (1988), who lament the low R^2 statistics of standard asset pricing models caused by high firm-specific stock return variation in the U.S. and other developed countries. If this reflects faster creative destruction in countries with better institutions, there is no cause for lamentation. Asset pricing models not only retain their basic validity, but may also find a new following among growth theorists as gauges of the intensity of creative destruction and related phenomena. Creative destruction is usually envisioned as creative innovators destroying laggards utterly; however, in practice, the laggards may only be beaten back for a while. Firm-specific performance heterogeneity may thus be a finer and more nuanced metric of the intensity of creative destruction than firm exit rates.

The paper is structured as follows. Section 2 describes our IT intensity, firm performance heterogeneity, and total factor productivity (TFP) measures. Section 3 covers regressions and Section 4 discusses interpretation and statistical robustness issues. Section 5 concludes with a brief discussion of the implications of our results.

2. Variable 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 4.

2.1. 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 two-digit industry.[2] Because we are interested in IT as a GPT in traditional sectors, we drop industries whose primary products are IT goods or services, specifically, 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 60 s) whose accounting data are incomparable and five agriculture and mining industries whose IT

[1] King and Levine (1993) provide empirical validation for the dependence of these firms on external financing. Fogel, Morck, and Yeung (2008) empirically link creative destruction to countries' financial development.

[2] Herman (2000) describes FRTW. Our industries resemble those in Hobijn and Jovanovic (2001) and Stiroh (2002). Fama and French (1997) partition manufacturing more finely and nonmanufacturing more coarsely, with 28 and 20 categories, respectively.

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 only after IT use intensifies. In this spirit, we use each industry's IT capital stock, 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

$$K_{i,k,t} = (1-\delta_k)K_{i,k,t-1} + I_{i,k,t}, \tag{1}$$

where δ_k is an asset-specific depreciation rate and $I_{i,k,t}$ is the industry's spending on type k assets that year. We set δ_k for IT to 0.31, as in the BEA FRTW data—see Fraumeni (1997).

We define IT capital as seven classes of computer hardware (mainframe computers, personal computers, direct access storage devices, computer printers, computer terminals, computer tape drives, and computer storage devices) and three classes of software (pre-packaged, custom, and own-account software).

Industry i's *IT intensity* in year t is then its stock of IT capital relative to other capital, that is,

$$IT_{i,t} \equiv \frac{\sum_{k\in IT} K_{i,k,t}}{\sum_{k\notin IT} K_{i,k,t}}. \tag{2}$$

We aggregate heterogeneous assets in (2) using Törnqvist indexes, as recommended by Jorgenson and Griliches (1967).

2.2. Firm performance heterogeneity

We now describe our firm performance metrics: real sales growth and stock returns. The *quarterly real sales growth rate* of firm j in industry i is

$$g_{j,i,\tau} \equiv \frac{P^{-1}_{i,\tau}S_{j,i,\tau} - P^{-1}_{i,\tau-4}S_{j,i,\tau-4}}{\frac{1}{2}(P^{-1}_{i,\tau}S_{j,i,\tau} + P^{-1}_{i,\tau-4}S_{j,i,\tau-4})}, \tag{3}$$

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

Firm j's *stock return* during month τ is $r_{j,i,\tau}$, 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 metric in 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, Morck, and Yeung (2004) and regress

$$r_{j,i,\tau} = \alpha_{j,t} + \beta^m_{j,i,t} r_{m,\tau} + \beta^i_{j,i,t} r_{i,\tau} + \varepsilon_{j,i,\tau}, \tag{4}$$

where τ indexes the 12 monthly returns in year t. The value-weighted market and industry returns, $r_{m,\tau}$ and $r_{i,\tau}$, exclude firm j to prevent spurious correlations with industry performance in industries with few firms.

Sales growth regressions are identical to (4), but τ indexes quarterly performance over the 12 quarters up to and including those in year t. The analogs to $r_{m,\tau}$ and $r_{i,\tau}$ in these regressions are sales-weighted market and industry-level sales growth rates.

The sum of squared residuals, $SSE_{j,i,t}$, and model variation, $SSM_{j,i,t}$, from running (4) on the $n_{j,t}$ observations for firm j and year t aggregate to the *mean firm-specific variation*,

$$\sigma^2_{\varepsilon,i,t} \equiv \frac{\sum_{j\in i} SSE_{j,i,t}}{\sum_{j\in i} n_{j,t}}, \tag{5}$$

and *mean systematic variation*,

$$\sigma^2_{m,i,t} \equiv \frac{\sum_{j\in i} SSM_{j,i,t}}{\sum_{j\in i} n_{j,t}}, \tag{6}$$

of industry i for year t. Except in the robustness tests in Section 4.2.1, $n_{j,t} = 12$ for all firms. Firms with missing data are dropped. We require at least five firms in an industry.

An analog to the R^2 of (4) measures *mean systematic over total variation*, $\sigma^2_{\varepsilon,i,t} + \sigma^2_{m,i,t}$, as

$$R^2_{i,t} \equiv \frac{\sigma^2_{m,i,t}}{\sigma^2_{m,i,t} + \sigma^2_{\varepsilon,i,t}}. \tag{7}$$

Since *IT intensity* data exist for $t\in[1971, 2000]$, intersecting these data with those for *IT intensity* yield panels of 1,180 industry-years for stock return heterogeneity regressions on *IT intensity* and 1,010 for sales growth heterogeneity regressions. This final sample spans 41 industries, as we drop four (local and interurban passenger transit, pipelines except natural gas, miscellaneous repair services, and legal services) because of insufficient data to estimate firm-specific variation.

2.3. Total factor productivity

Schumpeter (1912) argues that creative destruction enhances economic efficiency, which we capture using *total factor productivity* (TFP) growth. We measure industry TFP growth in two ways. First, we construct TFP growth from industry-level BEA data; second, we construct TFP growth to reflect the productivity of our sample of firms. The BEA's TFP figures better reflect overall productivity growth in the industry, for they are based on government data covering all firms in the industry, including small and unlisted firms that do not appear in our sample. However, Davis, Haltiwanger, Jarmin, and Miranda (2006) report markedly different patterns of firm-level volatility in listed and unlisted firms. We therefore construct a second measure of TFP growth based on accounting data reported by the sample of listed firms used in constructing our other variables. The BEA measure is thus a more complete reflection of overall industry productivity, while our TFP growth estimate is a more precise reflection of the productivity of the firms used to construct our other variables.

We estimate each industry's TFP as value-added less labor and capital costs. Industry TFP growth is the change in log industry TFP levels. We use annual, rather than quarterly, data because the estimation technique requires data only disclosed annually. BEA industry-level TFP measures are calculated using value-added, labor cost, and labor force variables from BEA's GPO data and capital-related variables from the BEA's FRTW data. Compustat-based industry TFP measures are weighted averages of firm-level TFPs defined as

$$\ln(TFP_{i,t}) \equiv \sum_{j \in i} \mu_{j,i,t}[\ln(Y_{j,i,t}) - \gamma_{L,j,i,t}\ln(L_{j,i,t}) - \gamma_{K,j,i,t}\ln(K_{j,i,t})], \tag{8}$$

where $Y_{j,i,t}$ is the 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. The weight $\mu_{j,i,t}$ is firm j's nominal value-added ($V_{j,i,t}$) over total industry nominal value-added in year t, $V_{j,i,t}/\sum_{j \in i} V_{j,i,t}$.

Value-added, $V_{j,i,t}$, is *operating income before depreciation* (Compustat item 13) plus *labor and related expenses* (item 42) as in Brynjolfsson and Hitt (2003). To obtain real value-added, nominal value-added is deflated by industry i's two-digit GPO *value-added deflator*. Prior to 1977, these deflators are unavailable, so we use gross output and intermediate input prices from BLS *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 as the industry average ratio of benefits to total compensation using GPO data.

Labor force, $L_{j,i,t}$, is employees (item 29) and *labor cost share*, $\gamma_{L,j,i,t}$, is *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

$$W_{k,i,t} \equiv \frac{1 - \zeta_{k,t} - u_t z_{k,t}}{1 - u_t}(r_{i,t} + \delta_k - G_{k,t})q_{k,t}, \tag{9}$$

where $\zeta_{k,t}$ is the *effective rate of investment tax credit*, u_t is the *corporate income tax rate*, $z_{k,t}$ is the *present value of capital consumption allowances*, $r_{i,t}$ is the *nominal internal rate of return*, δ_k is the *depreciation rate*, $G_{k,t}$ is the *asset-specific capital gain*, and $q_{k,t}$ is an *investment deflator*. Tax variables are from the BLS. Using FRTW data on the asset composition of each industry-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 *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 is or as 20 years, whichever is less. Taking all of firm j's assets as $a_{j,t}$ years old, we deflate their PP&E with the FRTW industry deflator to estimate the firm's *real capital stock*, $K_{j,i,t}$. Firm j's *capital cost share*, $\gamma_{K,j,i,t}$, is one minus $\gamma_{L,j,i,t}$.

2.4. General patterns in the data

Fig. 1 shows *IT intensity* is broadly distributed and rises steadily across U.S. industries, consistent with a GPT.[3] By the 1990s, IT is intensively used in such traditional manufacturing and nonmanufacturing 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.[4] The introductory quote describing "*A wave of innovation across a broad range of technologies*" seems an apt portrayal of IT as a GPT.

Fig. 2 graphs the variance decomposition, with column heights representing average total variation across all industries for a given year and their shading breaking this into industry average *firm-specific variation* (white) and *systematic variation* (black), from (5) and (6), respectively. The R^2 measure is the black section as a fraction of the total height of the column, and is graphed separately against time in Fig. 3. Firm-specific variation in both performance metrics (stock returns and sales growth) rises substantially in absolute magnitude and relative to systematic variation. Figs. 2 and 3 use industry equal-weighted figures, but industry value-weighted figures also show similar patterns. Fig. 4 shows that this surge affects a broad swath of industries.

This across-the-board upsurge in the firm-specific performance variation measures supports the conclusion of Wei and Zhang (2006) that any explanation of rising firm-specific variation in stock returns must also permit a contemporaneous rise in firm-specific fundamentals variation. Thus, Xu and Malkiel's (2003) thesis of noise trading by increasingly important institutional investors

[3] Corroborating this, managers of about 2,000 firms spanning a broad cross-section of U.S. industries (National Science Foundation (NSF), 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, Rajiv, and Srinivasan (1997) report that IT in the U.S. Post Office mainly speeds up mail processing. Athey and Stern (2002) report that IT also speeds up emergency response systems.

[4] See footnote 9 in Section 3.2.2 below.

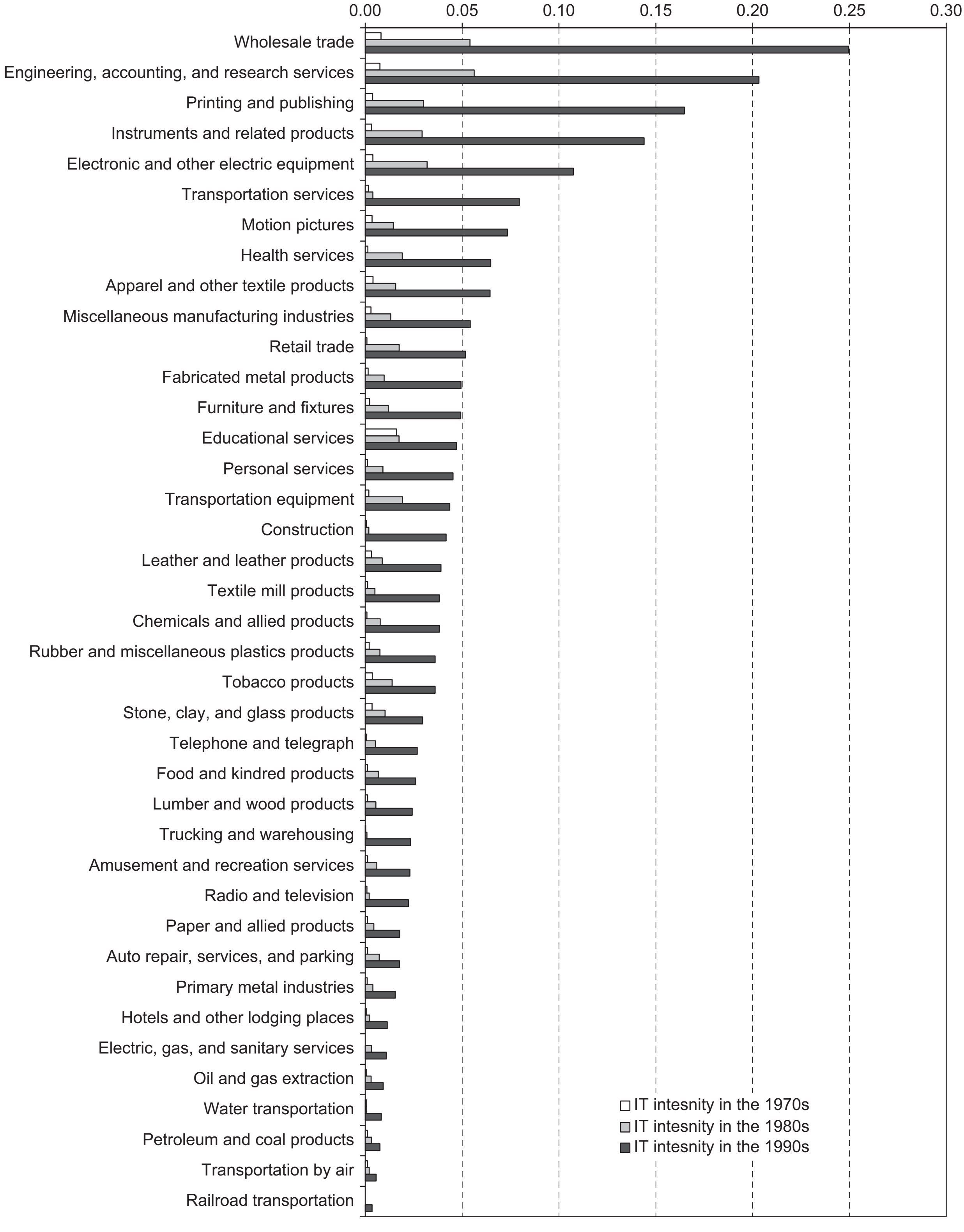

Fig. 1. Cross-industry distributions of IT intensities in the 1970s, 1980s, and 1990s in U.S. industries. Information technology (IT) intensity is computer hardware and software assets divided by other assets. Data are sorted by the average IT intensity of the 1990s.

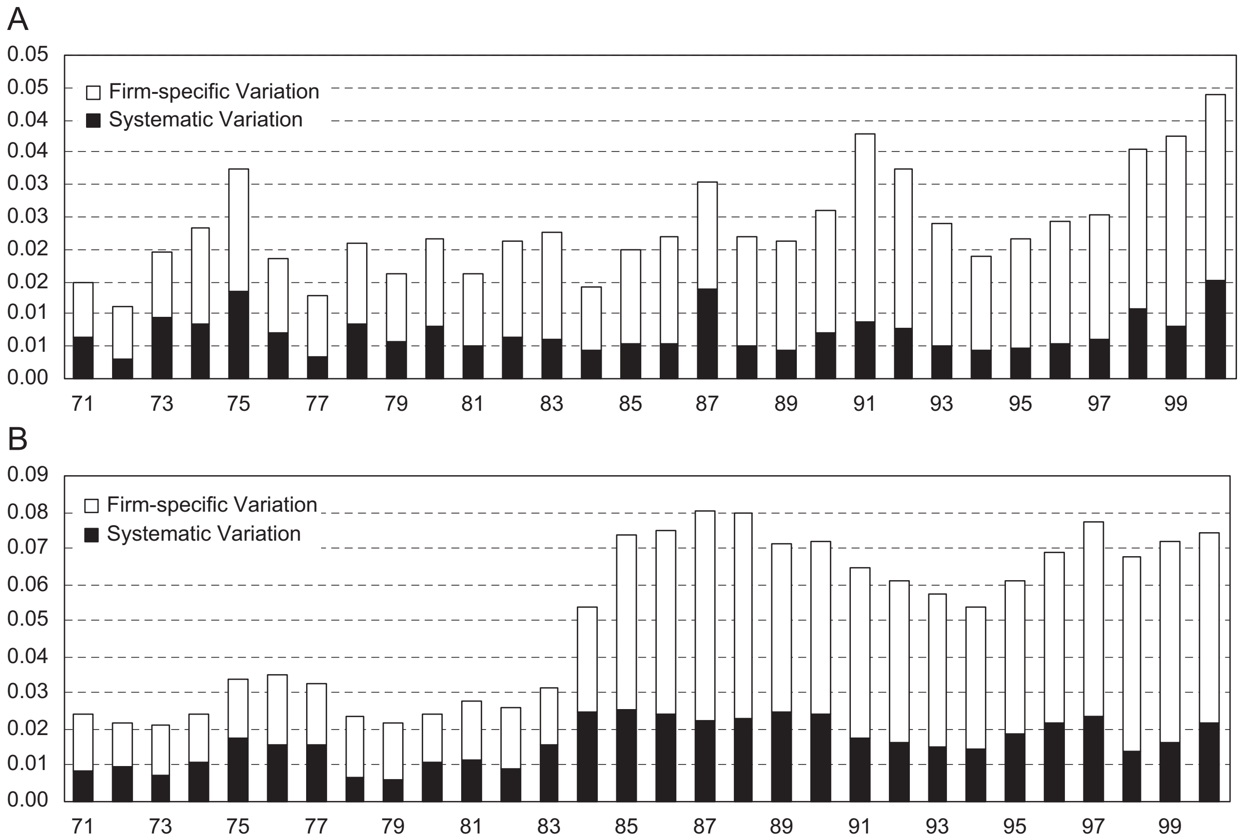

Fig. 2. Firm performance total variation and decomposition by year. Mean (industry equal-weight) total variation in firm-level performance decomposed into mean systematic (related to industry and economy factors) and mean firm-specific variation. Stock return variation is based on 12 monthly observations per year. Real sales growth variation is based on 12 quarterly observations from three-year rolling windows ending in the year indicated on the horizontal axis.

cannot be a complete explanation.[5] Nor can the Morck, Yeung, and Yu's (2000) suggestion of increasingly efficient firm-specific information capitalization because this does not necessitate a rise in firm-specific fundamentals variation. However, Fox, Morck, Yeung, and Durnev (2003), Bris, Goetzmann, and Zhu (2004), Durnev, Li, Morck, and Yeung (2004), Durnev, Morck, and Yeung (2004), Huang (2004), Li, Morck, Yang, and Yeung (2004), Ozoguz (2004), Jin and Myers (2006), Veldkamp and Wolfers (2007), 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 stimulated by financial system development and enhanced transparency (Schumpeter, 1912; King and Levine, 1993; Durnev, Li, Morck, and Yeung, 2004). That is, a new GPT, as explained in Jovanovic and Rousseau (2005), creates potentially value-increasing innovation and asset recombination opportunities. As firms compete to explore and exploit these opportunities, a functionally efficient stock market (Tobin, 1982) prices firms' individual probabilities of success, and allocates capital in an ex-ante microeconomically efficient way. Ex-post, as the process of creative destruction unfolds, upstarts and agile old firms unpredictably displace previous leaders and are in turn displaced by other upstarts or resurgent former leaders. This mechanically induces high firm-specific performance heterogeneity in fundamentals and stock returns, as winner and loser firms gradually emerge and are revealed. During this process, firm-level performance necessarily deviates from industry- and economy-level performance.

This reconciliation seems promising, for the IT intensity industry rankings in Fig. 1 correlate significantly with each of the firm performance heterogeneity industry ranks in Fig. 4. Fig. 5 plots the log of industry IT intensity against the logs of firm-specific variation in stock returns and in real sales growth. A clear positive correlation is apparent in both panels, and is statistically significant at conventional levels.

3. Regressions

Using U.S. industry panel data from 1971 to 2000, we regress firm performance heterogeneity on IT intensity

[5] See also Dennis and Strickland (2004).

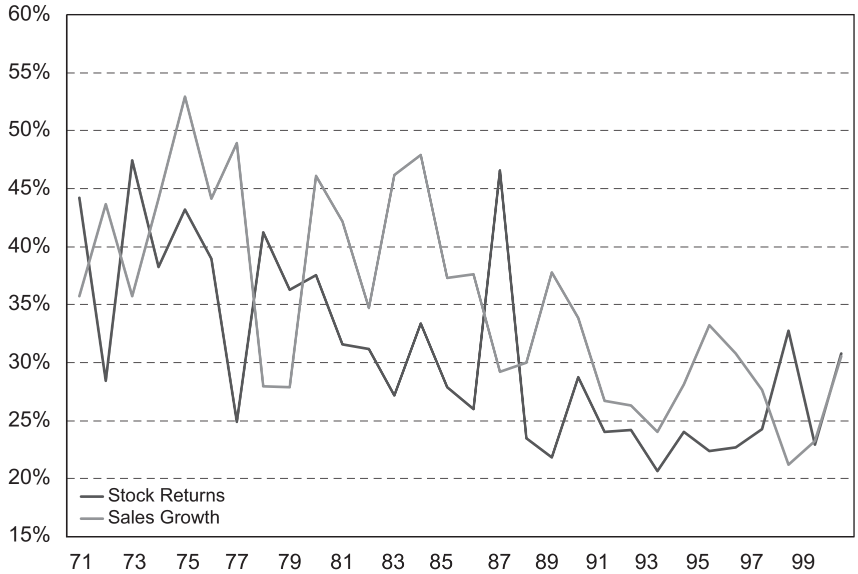

Fig. 3. Systematic variation in firm performance as fraction of total variation. The figure shows the fraction of variation in stock returns and in real sales growth explained by market and industry factors, averaged across all industries for each year.

and other relevant control variables. 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 4.

3.1. Firm performance heterogeneity dependent variables

To obtain near normal dependent variables, we take logs of (5) and (6). 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 (7) is bounded by the unit interval and is highly skewed, we apply a negative logistic transformation, as in Durnev, Morck, and Yeung (2004), to obtain *relative firm-specific variation*:

$$\psi_{i,t} \equiv \ln\left(\frac{1-R^2_{i,t}}{R^2_{i,t}}\right) = \ln(\sigma^2_{\varepsilon,i,t}) - \ln(\sigma^2_{m,i,t}). \quad (10)$$

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

3.2. Performance heterogeneity regressions

3.2.1. Basic setup

Using U.S. industry panel data, we estimate weighted least squares (WLS) regressions with time and industry fixed effects and estimate *t*-statistics allowing for heteroskedasticity and serial correlation clustered by industry.[6] Specifically, we run

$$\ln(\sigma^2_{\varepsilon,i,t}) = b_0 + b_1 \ln(IT_{i,t-1}) + CX_{i,t-1} + \sum_t \delta_t + \sum_i \lambda_i + u_{i,t}, \quad (11)$$

and

$$\psi_{i,t} = b_0 + b_1 \ln(IT_{i,t-1}) + CX_{i,t-1} + \sum_t \delta_t + \sum_i \lambda_i + u_{i,t}, \quad (12)$$

where the dependent variable is firm performance heterogeneity, *absolute* or *relative firm-specific variation* in stock returns and sales growth. Since sales variation reflects three-year windows, *IT intensity* is averaged across the prior three-year period in those regressions; it is intended to capture investment in the new GPT that leads to creative destruction. Stock returns heterogeneity is measured across annual windows, so those regressions use lagged annual *IT intensity*. Finally, *X* is a vector of controls, which we shall discuss in Section 3.2.2.

Using $\psi_{i,t}$ in (12) is equivalent to putting *absolute systematic variation* on the right-hand side and constraining its coefficient to unity. This suggests the more general specification

$$\ln(\sigma^2_{\varepsilon,i,t}) = b_0 + b_1 \ln(IT_{i,t-1}) + b_2 \ln(\sigma^2_{m,i,t-1}) + CX_{i,t-1} + \sum_t \delta_t + \sum_i \lambda_i + u_{i,t}. \quad (13)$$

For all regressions, the WLS weights are total assets in dollars—as of the prior year-end for stock return heterogeneity regressions, and averaged over the prior three years for sales growth heterogeneity regressions. Assets

[6] Obviously, clustering the standard errors of the industry fixed effect dummies' coefficients renders the covariance matrix singular. However, Arellano (1987) shows that invertiblity is restored if industry clustering is restricted to variables *other than* the industry fixed effects. See also Wooldridge (2002).

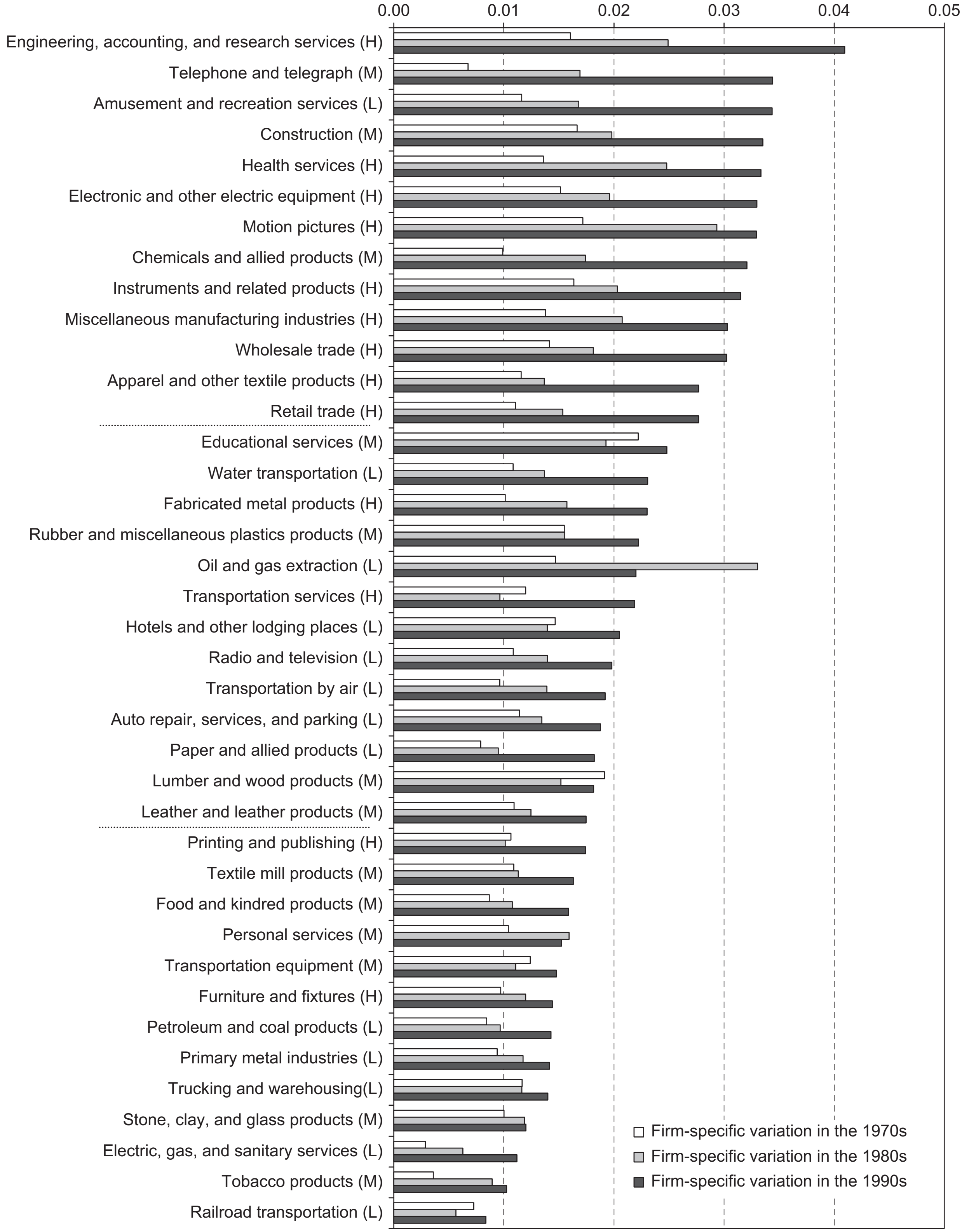

Fig. 4. Cross-industry distributions of firm-specific stock return variation in the 1970s, 1980s, and 1990s. Industries are sorted by the 1990s' firm-specific variation. *H* indicates industries with IT intensity in the top tertile of the sample for that decade. *M* and *L* indicate industries in the middle and lower tertiles, respectively.

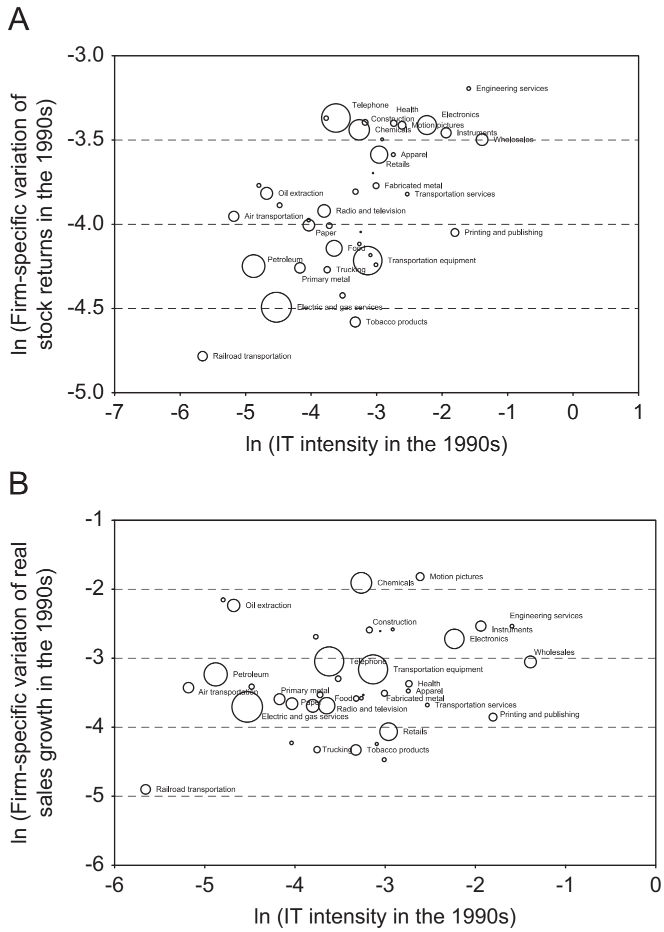

Fig. 5. Firm-specific performance variation and IT intensity. These graphs plot the log of average IT intensity in the 1990s (*x*-axis) against the log of average firm-specific variation in the 1990s (*y*-axis). The size of each bubble indicates the industry's total assets.

are econometrically desirable as weights because prior period sales or market capitalization might be correlated with current sales growth or stock returns, and in turn with heterogeneity measures constructed from these variables. Alternative weights are discussed in the robustness section below. WLS deprives small industries of undue influence. In our data, equal weights would give industries with less than 5% of the assets a 30% weight in the regressions, and industries with less than 10% of the assets a 50% weight.

Time fixed effects, δ_t, remove common time trends and economy-wide effects such as macroeconomic shocks and institutional development. This is motivated by the findings of Bushman and Smith (2003), Fox, Morck, Yeung, and Durnev (2003), Jin and Myers (2006), and others, linking improved accounting and financial transparency to increased firm-specific stock return variation, which might also correlate with more precisely targeted external funding of innovative firms.

We also include industry fixed effects, λ_i, because time-invariant effects correlated with industry IT intensity might affect performance heterogeneity. Their inclusion removes all purely cross-sectional variation from the analysis, possibly inappropriately diminishing the *t*-statistics of persistent independent variables genuinely related to performance heterogeneity. This conservative approach thus induces a bias against finding significant results.

We use industry clustering in estimating the standard errors of coefficients because some of our variables may be serially correlated within industries. For example, industries with elevated stock return heterogeneity one year may well have elevated stock return heterogeneity the next year too. The overlapping three-year windows used in constructing our sales growth heterogeneity measure further augment any pre-existing autocorrelation in those variables. Our construction of *IT intensity* using a perpetual inventory model may induce autocorrelation in that variable as well. Time-series autocorrelation in panel data leaves regression point estimates unbiased, but biases standard or Newey–West *t*-statistics upwards, even if fixed effects are included for both panel dimensions. Monte Carlo simulations by Petersen (2005) indicate that industry clustering produces unbiased standard errors in such cases. This technique for augmenting fixed effects with clustering is discussed in Arellano (1987) and Wooldridge (2002).

Table 1

Industry summary statistics: firm-specific performance heterogeneity and information technology intensity

Firm-specific performance variation by year is residual variation in firm-level regressions of total stock return and real sales growth rates on market and industry averages (weighted) of those variables. Industry and market 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, $\ln(\sigma_\varepsilon^2)$, and relative firm-specific variation, $\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2)$, are estimated using 12 monthly observations of stock return for each year. Real sales growth variation measures are constructed using 12 quarterly observations over three-year rolling windows. We only include firms with 12 month observations in case of stock returns and 12 quarterly observations in case of real sales growth. The sample period is 1971–2000. The sample comprises all firms in CRSP and Compustat in the 50 manufacturing and nonmanufacturing (approximately two-digit) industries excluding the finance sector (SIC 6000 to 6999). We exclude industries with fewer than five 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. In Panel B, numbers in parentheses are probability levels. Asterisks denote significance at 10% or better.

Panel A. Summary statistics

Firm performance heterogeneity measure	Mean	Median	Min.	Max.	Standard deviation	Sample size
Absolute firm-specific variation						
Stock returns	−4.279	−4.298	−6.520	−2.404	0.597	1,180
Sales growth	−3.801	−3.824	−6.676	−1.232	0.986	1,010
Relative firm-specific variation						
Stock returns	0.859	0.886	−1.025	3.122	0.528	1,180
Sales growth	0.697	0.707	−2.828	2.884	0.690	1,010
ln(*Information technology intensity*)	−5.135	−5.010	−10.587	−0.590	1.829	1,290

Panel B. Correlation coefficients

	Stock returns		Sales growth
	Absolute	Relative	Absolute
Stock returns			
Relative firm-specific variation	0.406* (0.000)		
Sales growth			
Absolute firm-specific variation	0.544* (0.000)	0.283* (0.000)	
Relative firm-specific variation	0.250* (0.000)	0.192* (0.000)	0.412* (0.000)

3.2.2. *Control variables*

We now turn to the main control variables we use in our multiple regressions. These variables, which are argued or shown elsewhere to explain heterogeneity in one or another firm performance metric, are as follows.

3.2.2.1. Corporate demography. Rising firm performance heterogeneity is linked to a rising proportion of small or young firms (Campbell, Lettau, Malkiel, and Xu, 2001; Pastor and Veronesi, 2003; Fama and French, 2004; Fink, Fink, Grullon, and Weston, 2005; Bennett and Sias, 2006; Davis, Haltiwanger, Jarmin, and Miranda, 2006; Brown and Kapadia, 2007). We therefore control for average firm age and size in each industry. In particular, *average firm age* is years since first appearance in CRSP, and *average firm size* is the log of average market capitalization or sales in regressions explaining firm-specific variation in returns or sales growth, respectively.[7]

The economics of why small or new firms should elevate performance heterogeneity is not fully understood. On the one hand, investors are possibly less informed about smaller and younger firms. Mechanically, news has a greater impact on investors' valuation of these firms than of older and more mature firms; and hence smaller and younger firms' stock return could be more volatile. Likewise, because of their newness and their smaller base, these firms' sales changes could be more volatile.

However, creative destruction may well underlie the linkage. Schumpeter (1912) and others argue that new, initially small, firms are better able to explore and exploit the opportunities brought about by new technology because innovators can better protect their property rights over their innovations by organizing their own firms. King and Levine (1993), Fogel, Morck, and Yeung (2008), and others provide empirical support for this view. Obviously, this does not imply that smaller firms are more efficient—indeed, Fama and French (2004) report a lower survival rate for smaller firms in the 1990s. This might reflect a greater sensitivity to economic shocks, as they suggest. But newly listed firms may also be the most enthusiastic early explorers and exploiters of a new GPT. Their ranks are therefore disproportionately likely to include both extreme winners and extreme losers.

To the extent that sensitivity to shocks differs systematically by firm size or age, controlling for corporate

[7] Replacing the averages with medians produces qualitatively similar results.

demography is warranted. However, if firm size and age are proxies for the propensity to undertake innovations, controlling for corporate demography might induce undesirable collinearity. In contrast, if IT intensity remains significant despite the inclusion of firm demography controls, or in regressions based on samples partitioned by firm age, its significance is unlikely to be an artefact of purely demographic explanations.

3.2.2.2. Competitive pressure. Intense competition is linked to elevated firm performance variation. We therefore control for each industry's *Herfindahl-Hirschman index*, based on annual firm sales from Compustat. For example, cutthroat price competition might magnify firm-specific shocks, turning minor setbacks into catastrophes and minor edges into lasting dominance (Philippon, 2003; Irvine and Pontiff, 2004; Comin and Mulani, 2006; Gaspar and Massa, 2006). Consistent with this view, low market power (Gaspar and Massa, 2006), recent deregulation (Irvine and Pontiff, 2004), and trade liberalization (Irvine and Pontiff, 2004; Li, Morck, Yang, and Yeung, 2004) are associated with more heterogeneous firm performance.[8]

A pure competition story justifies controls, but creative destruction and competition are interrelated. Schumpeter (1939) argues that creative destruction induces subsequent competition, as a new technology is standardized. Thus, Brown and Goolsbee (2002) find that internet sales reduce insurance premiums. It may also be the case that competition induces managers, desperate for any edge, to invest in innovation. Caves (1982) argues that foreign trade and investment often bring foreign ideas too and Li, Morck, Yang, and Yeung (2004) find elevated firm performance heterogeneity in countries open to the global economy. In spite of all of these interactions, if IT remains significant nonetheless, it is unlikely to be proxying for pure competition effects.

3.2.2.3. Research and development. IT is not the only investment that can lead to a technological edge. Schumpeter (1942), Romer (1986), and others stress innovation due to R&D spending by large established firms. Kothari, Laguerre, and Leone (2002) link R&D to future earnings variability, Chan, Lakonishok, and Sougiannis (2001) find similar results using stock returns, and Barron, Byard, Kile, and Riedl (2002) link high R&D to the lack of consensus in analysts' forecasts. We therefore control for 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, Lakonishok, and Sougiannis (2001). Our *R&D intensity* variable is then an industry's capitalized R&D over its PP&E (item 8).

We control for R&D because it might be both correlated to *IT intensity* and an alternative source of creative destruction. However, inspection of our variable shows that R&D capital is highly concentrated in a few industries and, within those, in the largest firms.[9] R&D thus seems an unlikely cause of an economy-wide firm performance heterogeneity upsurge.

3.2.2.4. Corporate finance. A firm's leverage and liquidity might affect its firm-specific performance variation. Ceteris paribus, higher leverage mechanically raises 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, that is, additional firm heterogeneity unrelated to IT intensity. We therefore include *leverage*, industry short- and long-term debt over assets (Compustat annual items 9 plus 34 over 6), and *liquidity*, industry current assets over current liabilities (annual items 4 over 5).

All of this takes liquidity and leverage decisions as independent of investment decisions, but this may not be the case. High debt capacity permits more externally financed IT, and liquidity implies access to internal funds, and perhaps to external funds too. These interactions suggest possible collinearity between our financial variables and IT intensity. However, if they are unaffected, a role for creative destruction is more plausible.

In Section 4, where we discuss various interpretation and statistical robustness issues, we describe variants of the above controls as well as a substantial list of other controls variables—firm size distribution, advertising expenses, book to market ratios, capital investment, and others. Our findings are robust to all these alternatives.

3.2.3. Results

Table 2 correlates firm performance heterogeneity with *IT intensity* and other controls (Panel A) and correlations among our main control variables (Panel B). Both firm performance heterogeneity in stock return and sales growth are positively and statistically significantly correlated with *IT intensity*. The correlation between the performance heterogeneity measures and the controls have signs that mostly correspond to the interpretations above, but the significance levels are sporadic—and these are pooled panel p-levels, which are biased downward and thus overstate the significance of the correlations.

Table 3 reports results of regression analyses. The table shows that *IT intensity* is significantly correlated with absolute and relative firm-specific performance heterogeneity in stock returns and sales growth, regardless of the controls included.[10] The *IT intensity* coefficients are

[8] Acemoglu (2005) notes that deregulation is a sectoral phenomenon affecting, e.g., transportation and utilities, but not already lightly regulated industries, and so argues that it cannot fully explain rising economy-wide firm-level volatility.

[9] 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). Survey data (NSF, 1999) reports that 19 of the 20 firms with R&D spending above 1 billion dollars reside in four manufacturing industries—IBM and Hewlett-Packard are in *industrial machinery*; GE, Lucent, and Intel are in *electric and electronic equipment*; GM and Ford are in *transportation equipment*; and Johnson & Johnson and Pfizer are 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.

[10] The only exception is the last column, where relative firm-specific variation of sales growth rates is used as the dependent variable in

Table 2
Correlation coefficients

IT intensity, *IT*, is the ratio of IT capital (computers and software) to other capital. *Age* is the average age of firms in an industry based on years listed in CRSP. *Size* is average market capitalization or sales of a firm in an industry, respectively. *Herfindahl* index is sales-based. *R&D* is estimated R&D capital stock over PP&E. *Leverage* is short-term plus long-term debt over total assets. *Liquidity* is current assets over current liabilities. Numbers in parentheses are probability levels at which the null hypothesis of zero correlation can be rejected. Asterisks denote significance at 10% or better.

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

	Stock returns		Sales growth		ln(IT)
	Absolute	Relative	Absolute	Relative	
Information technology					
ln(*IT*)	0.536*	0.451*	0.511*	0.382*	
	(0.000)	(0.000)	(0.000)	(0.000)	
Corporate demography					
ln(*Age*)	−0.369*	−0.021	−0.220*	0.006	−0.001
	(0.000)	(0.472)	(0.000)	(0.857)	(0.974)
ln(*Size*)	−0.017	0.183*	0.005	0.115*	0.265*
	(0.566)	(0.000)	(0.867)	(0.000)	(0.000)
Competition					
Herfindahl	−0.007	0.048	−0.040	0.023	−0.085*
	(0.823)	(0.103)	(0.205)	(0.461)	(0.003)
Technology					
ln(1+*R&D*)	0.249*	0.066*	0.266*	0.060*	0.238*
	(0.000)	(0.023)	(0.000)	(0.056)	(0.000)
Financing					
Leverage	0.030	0.031	0.102*	0.092*	−0.124*
	(0.305)	(0.285)	(0.001)	(0.004)	(0.000)
Liquidity	−0.058*	−0.073*	−0.102*	−0.106*	−0.004
	(0.046)	(0.013)	(0.001)	(0.001)	(0.896)

Panel B. Correlations of control variables with each other

	Corporate demography		Competition	Technology	Financing
	ln(*Age*)	ln(*Size*)	*Herfindahl*	ln(1+*R&D*)	*Leverage*
Corporate demography					
ln(*Size*)	0.506*				
	(0.000)				
Competition					
Herfindahl	−0.428*	−0.225*			
	(0.000)	(0.000)			
Technology					
ln(1+ *R&D*)	−0.074*	−0.038	−0.042		
	(0.009)	(0.176)	(0.138)		
Financing					
Leverage	−0.194*	−0.118*	0.227*	−0.209*	
	(0.000)	(0.000)	(0.000)	(0.000)	
Liquidity	−0.037	−0.349*	0.061*	0.108*	−0.440*
	(0.192)	(0.000)	(0.029)	(0.000)	(0.000)

highly significant across specifications. In contrast, other controls' coefficients, except for average firm size, are quite temperamental, with inconsistent signs and significance levels. This suggests that IT is the underlying factor most consistently associated with elevated firm-specific performance heterogeneity, and that the explanations associated with the various controls reflect aspects of this deeper explanation.

(*footnote continued*)
multiple regressions. However, no other variable has a significant coefficient except for Herfindahl index, which has the wrong sign. We also examine regressions on IT with the control variables used one-at-a-time. Results are qualitatively similar to the case of all controls.

Table 3 reveals that *firm age* is negative and significant if the dependent variables are absolute or relative firm-specific stock return heterogeneity. In regressions explaining sales growth heterogeneity, *firm age* is negative, but only significantly so in regressions including lagged systematic variation, $\ln(\sigma^2_{m,i,t-1})$.

The Herfindahl index, which proxies for competition, is insignificant in explaining absolute stock return heterogeneity and has the wrong, albeit significant, sign in explaining relative stock return heterogeneity. It is significant and has the expected sign in explaining absolute firm-specific performance heterogeneity in sales growth, but has the wrong sign in explaining relative firm-specific heterogeneity.

Table 3

Panel regressions of firm-specific performance heterogeneity on IT intensity and controls, with time and industry fixed effects

Dependent variables are industry-level measures of firm-specific heterogeneity in stock returns or sales growth rates. Within each set, the first four columns have absolute firm-specific variation $\ln(\sigma_\varepsilon^2)$ as their dependent variables; while the last two columns use relative firm-specific variation, $\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2)$, where $\ln(\sigma_m^2)$ is absolute systematic variation. IT intensity, *IT*, is the ratio of IT capital (computers and software) to other capital. *Age* is the average age of firms in an industry, defined as years listed in CRSP. *Size* is the average market capitalization or sales of the firms in each industry in the returns and sales growth heterogeneity regressions, respectively. The *Herfindahl* index is sales-based. *R&D* is estimated R&D capital stock over PP&E. *Leverage* is short plus long-term debt over total assets. *Liquidity* is current assets over current liabilities. Stock return variation is estimated using 12 monthly observations each year. Real sales growth variation is constructed using 12 quarterly observations over three-year rolling windows. In constructing variation measures, firms with fewer than 12 observations are excluded. IT intensity and controls are lagged by one year for returns variation regressions, and averaged over lagged three-year windows for sales growth variation regressions. All regressions include time and industry fixed effects. Observations are weighted by lagged total assets in the returns variation regressions and average industry total assets over lagged three year windows for sales growth variation regressions. The sample period is 1971–2000. The sample excludes IT-producing industries, finance industries (SIC 6000 to 6999), industries with fewer than five firms, and industries whose IT capital is ill defined. Numbers in parentheses are probability levels for rejecting the null hypothesis of a zero coefficient, based on *t*-statistics adjusted for industry clustering to eliminate bias due to serial dependence within industries. Asterisks denote significance at 10% or better.

	Stock returns						Sales growth					
	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific
Information technology												
ln(*IT*)	0.256*	0.202*	0.216*	0.180*	0.105*	0.096*	0.323*	0.202*	0.242*	0.176*	0.106*	0.106
	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.003)	(0.000)	(0.046)	(0.021)	(0.015)	(0.038)	(0.128)
Corporate demography												
ln(*Age*)		−0.345*		−0.302*		−0.149*		−0.744		−0.659*		−0.058
		(0.086)		(0.076)		(0.087)		(0.165)		(0.057)		(0.672)
ln(*Size*)		−0.173*		−0.155*		−0.163*		−0.424*		−0.295*		0.004
		(0.045)		(0.023)		(0.001)		(0.074)		(0.047)		(0.973)
Competition												
Herfindahl		−0.764		−0.250		1.120*		−2.348*		−4.052*		1.314*
		(0.261)		(0.681)		(0.002)		(0.000)		(0.000)		(0.001)
Technology												
ln(1+*R&D*)		0.012		0.323		−1.135*		−0.595		1.492*		−0.219
		(0.982)		(0.486)		(0.000)		(0.530)		(0.017)		(0.740)
Financing												
Leverage		−1.587*		−1.228*		−0.356		−3.439*		−2.529*		−0.943
		(0.007)		(0.011)		(0.192)		(0.002)		(0.000)		(0.137)
Liquidity		0.149		0.158		0.127*		−0.188		−0.295		−0.173
		(0.293)		(0.162)		(0.098)		(0.607)		(0.304)		(0.575)
Systematic variation												
Absolute systematic			0.264*	0.196*					0.292*	0.167*		
			(0.000)	(0.000)					(0.000)	(0.001)		
Adjusted R^2	0.773	0.801	0.784	0.800	0.639	0.653	0.705	0.757	0.737	0.787	0.466	0.474
Sample size	1,180	1,180	1,142	1,142	1,180	1,180	1,010	1,010	930	930	1,010	1,010

The *R&D intensity* variable is only sporadically significant and attracts economically inconsistent signs in explaining firm-specific performance heterogeneity. Overall, *R&D intensity* does not detract from IT in explaining elevated firm performance heterogeneity in the U.S. in recent decades.

These results are encouraging: they suggest that firm-specific performance heterogeneity is related to more intensive use of information technology (IT), a recently developed general purpose technology that stimulates creative destruction.

3.3. Productivity regressions

We suggest that the relation between firm performance heterogeneity and IT intensity reflects a creative destruction process that stems from the advent of IT, a general purpose technology. As such, firm-specific performance heterogeneity should presage TFP growth.[11] Moreover, if IT accelerates TFP growth by fuelling creative destruction, including firm performance heterogeneity should diminish the coefficient and significance of IT in regressions explaining TFP growth.

The time horizon over which TFP growth is measured is important because Schumpeter (1912) explicitly links creative destruction to medium and long-run growth, and explicitly disallows a link with short-run growth. Annual windows are thus certainly too short; but, a very long window, such as 1971–2000, allows only a single cross-section regression on a somewhat reduced sample of industry observations. Unobserved industry factors also become more treacherous in the latter exercise because

[11] Consistent with this, Durnev, Li, Morck, and Yeung (2004) use country-level data to show that higher firm-specific stock return variation correlates with higher national TFP growth.

industry fixed effects obviously cannot be included. We therefore follow the common practice in the productivity literature—see Beck, Levine, and Loayza (2000) and, Aghion, Angeletos, Banerjee, and Manova (2004), and others—of defining the *medium-run* as five years and estimating productivity growth across windows of that length. We revisit longer window lengths as robustness checks. The five-year windows give us a 235 observation industry-time panel of TFP growth rates defined as ${}_{TFP}g_{i,t} = \ln(TFP_{i,t}) - \ln(TFP_{i,t-4})$, where $TFP_{i,t}$ is industry i's TFP level in year t, from (8).

Our WLS regressions of productivity growth are of the form

$$ {}_{TFP}g_{i,t} = c_0 + c_1\overline{\ln(\sigma^2_{\varepsilon,i,t-5})} + c_2\overline{\ln(\sigma^2_{m,i,t-5})} + c_3\ln(TFP_{i,t-4}) + \sum_t \delta_t + \sum_i \lambda_i + \omega_{i,t} \tag{14} $$

and

$$ {}_{TFP}g_{i,t} = c_0 + c_1\overline{\psi_{i,t-5}} + c_3\ \ln(TFP_{i,t-4}) + \sum_t \delta_t + \sum_i \lambda_i + \omega_{i,t}, \tag{15} $$

where $\overline{\ln(\sigma^2_{\varepsilon,i,t-5})}$, $\overline{\ln(\sigma^2_{m,i,t-5})}$, and $\overline{\psi_{i,t-5}}$ are industry absolute firm-specific, absolute systematic, and relative firm-specific stock return variation averaged over the five-year window $t-9$ to $t-5$[12] prior to that used to estimate ${}_{TFP}g_{i,t}$. The inclusion of absolute systematic variation in (14) is motivated by Ramey and Ramey's (1995) cross-country study, which shows that aggregate volatility has a negative impact on economic growth.

We focus on firm-specific stock return heterogeneity as gauging the pace of creative destruction because stock returns are more forward looking than sales growth rates, and therefore arguably more prescient of subsequent longer-term outcomes. Stock return heterogeneity is also constructed from higher frequency data, and therefore may be estimated more precisely.

We control for the log of the industry's TFP level at the beginning of each TFP growth estimation window, $\ln(TFP_{i,t-4})$, because "catching up" across industries might raise TFP growth in industries with lower initial TFP levels. However, if industry TFP growth converges to economy average rates—see, e.g., Bernard and Jones (1996) regarding this debate—the error terms in our panel regressions might be correlated with TFP levels. Our panel, with only 41 industries, is too small for the GMM solutions to this quandary proposed by Arellano and Bond (1991) and applied by Beck, Levine, and Loayza (2000). We therefore run (14) and (15) both with and without $\ln(TFP_{i,t-4})$ to check the sensitivity of our results. The two sets of results are very similar. To save space, we report only the set in which $\ln(TFP_{i,t-4})$ is included.

As before, time fixed effects mitigate the influence of macroeconomic shocks and common time trends. Since latent industry characteristics also may affect TFP growth, we also include industry fixed effects and use industry clustering to obtain serial correlation and heteroskedasticity-consistent t-statistics, as in Arellano (1987) and Wooldridge (2002). Also as in the regressions in Table 3, we weight observations by industry size. The weights are industry total dollars of assets averaged over the prior five-year window, from $t-9$ to $t-5$.

These regressions, presented in Panels A and B of Table 4, clearly show that industries with higher firm performance heterogeneity in stock returns post economically and statistically significantly faster subsequent TFP growth. In Panel A, the TFP growth rates are BEA industry-level figures, while the Panel B growth rates are calculated from our sample firms, as described in Section 2.3. The coefficients are smaller in the BEA measure regressions, but exhibit the same pattern of signs and statistical significance.

Note how controlling for IT intensity leaves firm-specific performance heterogeneity qualitatively unaffected. In contrast, IT intensity fades when performance heterogeneity is present. Regressions of TFP growth on initial TFP levels and IT intensity only (third columns in Panels A and B) assign the latter significant coefficients of 0.073 for BEA-based TFP growth, or 0.224 for Compustat-based TFP growth. But Table 4 shows IT intensity entirely insignificant in otherwise identical regressions of BEA-based TFP growth that also contain performance heterogeneity. In regressions explaining Compustat-based TFP growth, the IT intensity coefficient is cut in half and its significance level is also substantially reduced.

4. Robustness checks

A range of alternative approaches produce qualitatively similar results, by which we mean patterns of signs and significance for variables of interest identical to those in the tables.

4.1. *The robustness of our interpretation*

We subject our interpretation to a series of robustness checks both in terms of economics and statistics. We also examine robustness in terms of variable constructs and regression specifications.

4.1.1. *Sample composition*

One issue is that our data are based on *listed firms*, that is, those in Compustat. Recently, Davis, Haltiwanger, Jarmin, and Miranda (2006) report that increased firm volatility appears restricted to publicly traded firms. Our sample's total sales represents, on average, about half of U.S. GDP through the period of 1971–2000, rising from about 40% in early years to about 60% in later years.[13] Thus, our results need not carry to unlisted firms. However, Schumpeter (1912) explicitly notes that entrepreneurs often require external equity financing; recent empirical work, surveyed in Levine (1997, 2005), confirms this. As a result, effects associated with creative destruction might well be more evident in listed firms, consistent

[12] Section 4.3 confirms robustness to alternative windows.

[13] Since Compustat sales include intermediate goods as well as value-added, these are not directly comparable to the U.S. GDP. To adjust for this problem in making these comparisons, we multiply average sales by the average share of value-added in sales.

Table 4
Panel regressions of TFP growth on firm-specific performance heterogeneity and controls, with time and industry fixed effects

Panel data are U.S. industries followed from 1971 to 2000, across six non-overlapping five-year intervals (1971–1975, …, 1996–2000). The dependent variable is industry TFP growth rate during each five-year interval. Initial TFP is measured at the beginning year at each interval. Performance heterogeneity measures and IT intensity are the average of values over the prior five-year interval, ($t-9$, $t-5$). All regressions include time and industry fixed effects. Observations are weighted by the industry's total assets, averaged over the prior window. The sample excludes IT-producing industries, finance industries (SIC 6000 to 6999), and industries with fewer than five firms available for constructing TFP growth rates or performance heterogeneity measures, as well industries whose IT capital is ill defined. Panel A uses BEA industry-level TFP figures; Panel B uses TFP measures constructed from Compustat firms. Numbers in parentheses are probability levels, based on t-statistics adjusted for industry clustering. Asterisks denote significance at 10% or better.

Panel A. TFP growth defined using BEA industry-level data

	4a.1	4a.2	4a.3	4a.4	4a.5
Performance heterogeneity					
Absolute firm-specific return variation, $\ln(\sigma_\varepsilon^2)$	0.195*			0.147*	
	(0.001)			(0.092)	
Absolute systematic return variation, $\ln(\sigma_m^2)$	−0.105			−0.077	
	(0.272)			(0.328)	
Relative firm-specific return variation, $\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2)$		0.191*			0.131*
		(0.002)			(0.101)
Controls					
$\ln(IT)$			0.073*	0.037	0.046
			(0.030)	(0.473)	(0.282)
Initial $\ln(TFP)$	−0.140	−0.133	−0.133	−0.139	−0.134
	(0.316)	(0.324)	(0.297)	(0.306)	(0.305)
Adjusted R^2	0.693	0.690	0.690	0.694	0.693
Sample size	235	235	234	234	234

Panel B. TFP growth defined using Compustat sample firms

	4b.1	4b.2	4b.3	4b.4	4b.5
Performance heterogeneity					
Absolute firm-specific return variation, $\ln(\sigma_\varepsilon^2)$	0.643*			0.526*	
	(0.000)			(0.001)	
Absolute systematic return variation, $\ln(\sigma_m^2)$	−0.289			−0.214	
	(0.165)			(0.237)	
Relative firm-specific return variation, $\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2)$		0.637*			0.470*
		(0.001)			(0.003)
Controls					
$\ln(IT)$			0.224*	0.087*	0.126*
			(0.005)	(0.072)	(0.017)
Initial $\ln(TFP)$	−0.446*	−0.413*	−0.453*	−0.450*	−0.425*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.815	0.798	0.790	0.819	0.806
Sample size	235	235	234	234	234

with the findings reported by Davis, Haltiwanger, Jarmin, and Miranda (2006). However, we relegate attempts to understand the difference between private and publicly traded firms to future research, and we caution that our results are based *only* on publicly traded firms.

A second issue relates to *firm age*, as other recent work links high firm volatility to a rising proportion of relatively recently listed firms (e.g., Campbell, Lettau, Malkiel, and Xu, 2001; Pastor and Veronesi, 2003; Fama and French, 2004; Fink, Fink, Grullon, and Weston, 2005; Bennett and Sias, 2006; Davis, Haltiwanger, Jarmin, and Miranda, 2006; Brown and Kapadia, 2007). As noted above, young listed firms might tend to include more energetic innovators, so these findings are not inconsistent with our thesis. But creative destruction should affect old firms too. To explore this, we rerun Table 3, partitioning the sample into young and old firms.

Our median firm has been listed for eight years, so we partition the sample at *age* = 8 years, where *age* is the difference between year t and the firm's listing year. The young firm subsample has a mean age of 3.64, a maximum age of 7.0, a median of 3.0, and a minimum 1.0. The old firm sample has a mean age of 19.03, a maximum of 54.0, a median of 16.0, and a minimum of 8.0 years.

Panels A and B of Table 5 report regression results for young and old firms, respectively. The findings are broadly comparable across subsamples. IT intensity is significantly related to absolute heterogeneity in stock returns and sales growth rates in both the young and old subsamples.

Table 5

Panel regressions of firm-specific performance heterogeneity on IT intensity and controls, with time and industry fixed effects, for separate new and old firm subsamples

Dependent variables are industry-level measures of firm-specific heterogeneity in stock returns or sales growth rates. Within each set, the first four columns have absolute firm-specific variation $\ln(\sigma_\varepsilon^2)$ as their dependent variables; while the last two columns use relative firm-specific variation, $\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2)$, where $\ln(\sigma_m^2)$ is absolute systematic variation. IT intensity, *IT*, is the ratio of IT capital (computers and software) to other capital. *Age* is the average age of firms in an industry, defined as years listed in CRSP. *Size* is the average market capitalization or sales of the firms in each industry in the returns and sales growth heterogeneity regressions, respectively. The *Herfindahl* index is sales-based. *R&D* is estimated R&D capital stock over PP&E. *Leverage* is short- plus long-term debt over total assets. *Liquidity* is current assets over current liabilities. Stock return variation is estimated using 12 monthly observations each year. Real sales growth variation is constructed using 12 quarterly observations over three-year rolling windows. In constructing variation measures, firms with fewer than 12 observations are excluded. IT intensity and controls are lagged by one year for returns variation regressions, and averaged over lagged three-year windows for sales growth variation regressions. All regressions include time and industry fixed effects. Observations are weighted by lagged total assets in the returns variation regressions and average industry total assets over lagged three-year windows for sales growth variation regressions. The sample period is 1971–2000. The sample excludes IT-producing industries, finance industries (SIC 6000 to 6999), industries with fewer than five firms, and industries whose IT capital is ill defined. Numbers in parentheses are probability levels for rejecting the null hypothesis of a zero coefficient, based on *t*-statistics adjusted for industry clustering to eliminate bias due to serial dependence within industries. Asterisks denote significance at 10% or better.

Panel A reports regression results for a young firm subsample, which contains firms younger than the median age of eight years as a listed firm in CRSP. Panel B reports regression results for an old firm subsample, which contains firms that have been listed in CRSP for eight years or more.

Panel A. New firm subsample

	Stock returns						Sales growth					
	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific
Information technology												
ln(*IT*)	0.407*	0.352*	0.325*	0.296*	0.082*	0.074*	0.442*	0.244*	0.293*	0.211*	0.115	0.116
	(0.002)	(0.000)	(0.001)	(0.001)	(0.027)	(0.012)	(0.000)	(0.067)	(0.005)	(0.064)	(0.128)	(0.209)
Corporate demography												
ln(*Age*)		−0.098		−0.041		−0.207*		−1.115*		−0.919*		0.126
		(0.639)		(0.826)		(0.081)		(0.029)		(0.004)		(0.705)
ln(*Size*)		−0.231*		−0.175*		−0.190*		−0.392		−0.303		0.085
		(0.054)		(0.072)		(0.008)		(0.156)		(0.172)		(0.451)
Competition												
Herfindahl		0.308		0.326		0.979*		3.422		2.368		0.563
		(0.738)		(0.691)		(0.003)		(0.368)		(0.461)		(0.696)
Technology												
ln(1+*R&D*)		−0.739		0.044		−0.797*		−0.046		1.606*		0.573
		(0.327)		(0.942)		(0.004)		(0.964)		(0.040)		(0.488)
Financing												
Leverage		−1.317*		−1.084*		−0.459*		−1.825*		−0.895		−1.549*
		(0.009)		(0.008)		(0.051)		(0.065)		(0.322)		(0.005)
Liquidity		0.418*		0.342*		0.012		0.364		−0.147		−0.215
		(0.080)		(0.100)		(0.870)		(0.195)		(0.504)		(0.467)
Systematic variation												
Absolute systematic			0.204*	0.161*					0.161*	0.118*		
			(0.008)	(0.003)					(0.004)	(0.005)		
Adjusted R^2	0.654	0.685	0.646	0.664	0.547	0.557	0.700	0.727	0.712	0.729	0.417	0.421
Sample size	1,055	1,055	1,025	1,025	1,055	1,055	793	793	706	706	793	793

Panel B. Old firm subsample

Information technology												
ln(*IT*)	0.152*	0.079*	0.131*	0.082*	0.060	0.059	0.322*	0.245*	0.284*	0.222*	0.210*	0.186*
	(0.004)	(0.025)	(0.004)	(0.037)	(0.320)	(0.185)	(0.025)	(0.056)	(0.091)	(0.054)	(0.012)	(0.029)
Corporate demography												
ln(*Age*)		−0.368		−0.307		−0.025		−0.435		−0.499		−0.259
		(0.210)		(0.204)		(0.822)		(0.407)		(0.181)		(0.285)
ln(*Size*)		−0.238*		−0.243*		−0.214*		−0.165		−0.113		0.096
		(0.028)		(0.005)		(0.000)		(0.566)		(0.649)		(0.365)
Competition												
Herfindahl		−0.935*		−0.349		1.146*		−4.414*		−6.008*		0.635
		(0.093)		(0.465)		(0.007)		(0.000)		(0.000)		(0.185)
Technology												
ln(1+*R&D*)		1.332*		1.392*		−0.881*		−0.522		1.994*		0.189
		(0.006)		(0.002)		(0.002)		(0.647)		(0.051)		(0.798)
Financing												
Leverage		−1.096*		−0.669		−0.009		−3.520*		−3.029*		−1.446*
		(0.071)		(0.135)		(0.968)		(0.029)		(0.010)		(0.022)
Liquidity		0.304*		0.310*		0.162*		−0.445		−0.520		−0.122
		(0.070)		(0.022)		(0.083)		(0.279)		(0.112)		(0.680)
Systematic variation												
Absolute systematic			0.319*	0.226*					0.161*	0.087		
			(0.000)	(0.000)					(0.065)	(0.124)		
Adjusted R^2	0.783	0.818	0.807	0.827	0.673	0.687	0.513	0.564	0.509	0.578	0.379	0.382
Sample size	1,100	1,100	1,066	1,066	1,100	1,100	949	949	868	868	949	949

Relative stock return heterogeneity is significant only for young firms, but relative sales growth heterogeneity is significant only for old firms. Our result is thus clearly not driven by younger firms in general.

To confirm explicitly that our finding is not an artifact of 1990s listings, we partition our sample at $age = 10$ years, that is, into firms listed before versus in or after 1990. This expands the young firm subsample to 56% of the total, but shrinks the old firm subsample to only 44%. The results for stock return heterogeneity are qualitatively unaffected. However, our sales growth heterogeneity results are now weaker in the old firm subsample, with only three significant coefficients in six cases, and stronger in the young firms subsample, with significance in all six specifications. The weaker old firm results are likely, in part at least, due to the smaller sample size because splitting at five years generates the opposite effect: Weaker sales growth results for young firms (significance in four of six cases) and stronger findings for old firms (significance in five of six cases). Again, the stock returns findings are preserved in both subsamples.

Our result is thus clearly driven by neither 1990s listings nor young firms in general. Therefore, while our finding would have been perfectly consistent with elevated firm-specific volatility primarily in newly listed firms, it is more general.[14]

4.1.2. Reverse causality and endogeneity?

Reverse causality of at least two genres might arise. One genre is not necessarily connected with creative destruction. For example, exogenous productivity shocks might well induce performance heterogeneity and IT investment might help firms cope with increased uncertainty.[15] If the productivity shocks are positive on average, we might also observe accelerated productivity.

A second genre of reverse causality arguments stems directly from our main hypothesis relating enhanced firm-specific performance heterogeneity to an intensification of the process of creative destruction. In a recently discovered "lost" seventh chapter of Schumpeter (1912), Schumpeter (2002) stresses that creative destruction is a process, "not with a causal chain of explanation" (p. 98), and goes on to describe a circular flow (what would now be called a positive feedback loop) with explicitly bidirectional causality. Innovation raises productivity, but the successes of past innovators in raising productivity also inspire the next generation of innovators. Thus, reverse causality is consistent with our hypothesis. Our task is to confirm direct causality, rather than to reject reverse causality.

To do this, we must ensure that our independent variables capture only expected growth, and that the residuals are uncorrelated with the independent variables, lest well-known endogeneity problems arise. To preclude such problems, we employ instrumental variables for IT intensity. These must be highly correlated with IT intensity, but uncorrelated with the true regression residuals.

Since our sample excludes industries that produce IT assets, we select instruments associated with the supply of IT assets. As with capital investment in general, IT intensity should be related to past IT intensity and the cost of new IT assets. We proxy for the latter using the estimated marginal cost of IT (quality) production and IT tax rates, and use these proxies as our instruments.[16]

Since marginal IT production costs are unobservable, we estimate approximations. In doing so, we take special care to eliminate any possible effects on marginal cost from demand side factors. Following Chun and Nadiri (2008), we construct the marginal cost of *computer quality* since this mainly depends on the efficiency of R&D expenditures in the IT-producing sector, rather than demand-side factors. We measure the quality of computers as the ratio of list (unit) prices to hedonic prices, and calculate the marginal cost of quality by estimating a flexible cost function.[17] Finally, we multiply this marginal cost by each industry's beginning-of-year IT intensity to estimate marginal cost of IT (quality) production costs for each sector.

We estimate IT tax rates using asset-specific tax parameters. These are tax-related components of the rental price of capital, defined as $Tax_{k,t} \equiv (1 - \zeta_{k,t} - u_t z_{k,t})/(1 - u_t)$ for asset k at time t, with $\zeta_{k,t}$ the effective rate of the investment tax credit, u_t the corporate income tax rate, and $z_{k,t}$ the present value of a dollar of tax depreciation allowances. These variables, in turn, are all from the BLS. Using the IT asset composition of each industry-year, we aggregate our IT tax parameters using the Törnqvist method.

Well-known weak instruments problems can seriously bias instrumental variables techniques of the sort we undertake, even in large samples. Our tax rate and marginal cost pass standard weak instruments test criteria, and thus are acceptable as instrumental variables.[18]

[14] Schumpeter (1942) posits that older firms may participate in races to innovate, and may even have an advantage over younger firms if huge capital outlays are required and public equity is expensive.

[15] Note that IT intensity is defined as IT capital over non-IT capital, and that this ratio could still be exogenous if TFP shocks have equal effects on IT and non-IT investment. However, different effects permit endogeneity, and seem not implausible a priori.

[16] We are most grateful to an anonymous referee for suggesting this procedure.

[17] Hedonic and list prices are from the BEA's FRTW data and the Census Bureau's *Current Industrial Reports*, respectively. Assuming a translog cost function including both the quality and quantity of computers, the marginal costs of quality and quantity are estimated separately. See Chun and Nadiri (2008) for details.

[18] First, our first-stage F-statistics are on average larger than 350, which is much greater than the approximate cutoff of 10 for weak instruments suggested by Stock and Yogo (2005). Second, we perform Anderson–Rubin confidence test to check the significance of the second-stage regression. This test is valid whether instruments are strong, weak, or even irrelevant. Third, we estimate the second-stage coefficient using the Limited Information Maximum Likelihood (LIML) method suggested by Stock, Wright, and Yogo (2002) and implemented by Moreira and Poi (2003). Anderson–Rubin tests show that LIML coefficients are not statistically different from Two-Stage Least Squares (2SLS) coefficients. We are grateful for Prof. James Stock for many helpful comments and suggestions on the issue of weak instruments.

Table 6

Two-stage panel regressions of firm-specific performance heterogeneity on IT intensity and controls, with time and industry fixed effects

Dependent variables are industry-level measures of firm-specific heterogeneity in stock returns or sales growth rates. Within each set, the first four columns have absolute firm-specific variation $\ln(\sigma_\varepsilon^2)$ as their dependent variables; while the last two columns use relative firm-specific variation, $\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2)$, where $\ln(\sigma_m^2)$ is absolute systematic variation. IT intensity, defined as IT capital assets (computers and software) over other capital assets, is estimated in a first-stage regression with *IT tax rates* and the *marginal cost of IT (quality) production* as instrumental variables. The control variables are as follows: *Age* is the average age of firms in an industry, defined as years listed in CRSP. *Size* is the average market capitalization or sales of the firms in each industry in the returns and sales growth heterogeneity regressions, respectively. The *Herfindahl* index is sales-based. *R&D* is estimated R&D capital stock over PP&E. *Leverage* is short plus long-term debt over total assets. *Liquidity* is current assets over current liabilities. Stock return variation is estimated using 12 monthly observations each year. Real sales growth variation is constructed using 12 quarterly observations over three-year rolling windows. In constructing variation measures, firms with fewer than 12 observations are excluded. IT intensity and controls are lagged by one year for returns variation regressions, and averaged over lagged three-year windows for sales growth variation regressions. All regressions include time and industry fixed effects. Observations are weighted by lagged total assets in the returns variation regressions and average industry total assets over lagged three-year windows for sales growth variation regressions. The sample period is 1971–2000. The sample excludes IT-producing industries, finance industries (SIC 6000 to 6999), industries with fewer than five firms, and industries whose IT capital is ill defined. Numbers in parentheses are probability levels for rejecting the null hypothesis of a zero coefficient, based on *t*-statistics adjusted for industry clustering to eliminate bias due to serial dependence within industries. Asterisks denote significance at 10% or better.

	Stock returns						Sales growth					
	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific
Information technology												
ln(*IT*)	0.411*	0.334*	0.355*	0.307*	0.191*	0.151*	0.381*	0.117	0.291*	0.194*	0.182*	0.202*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)	(0.432)	(0.016)	(0.056)	(0.000)	(0.010)
Corporate demography												
ln(*Age*)		−0.274		−0.237		−0.160		−0.666		−0.618*		−0.148
		(0.151)		(0.149)		(0.122)		(0.192)		(0.070)		(0.514)
ln(*Size*)		−0.178*		−0.164*		−0.170*		−0.474*		−0.292*		0.056
		(0.041)		(0.023)		(0.001)		(0.065)		(0.072)		(0.673)
Competition												
Herfindahl		−0.948		−0.468		1.107*		−2.065*		−3.984*		1.295*
		(0.166)		(0.454)		(0.003)		(0.006)		(0.000)		(0.004)
Technology												
ln(1+*R&D*)		−0.161		0.199		−1.228*		−0.412		1.528*		−0.421
		(0.723)		(0.602)		(0.000)		(0.688)		(0.020)		(0.539)
Financing												
Leverage		−1.335*		−1.011*		−0.244		−3.202*		−2.236*		−0.878
		(0.024)		(0.036)		(0.400)		(0.003)		(0.000)		(0.191)
Liquidity		0.041		0.062		0.086		−0.119		−0.314		−0.262
		(0.804)		(0.639)		(0.155)		(0.787)		(0.357)		(0.393)
Systematic variation												
Absolute systematic			0.232*	0.178*					0.287*	0.170*		
			(0.001)	(0.000)					(0.000)	(0.001)		
Adjusted R^2	0.763	0.794	0.775	0.793	0.632	0.651	0.701	0.751	0.732	0.783	0.464	0.472
Sample size	1,180	1,180	1,142	1,142	1,180	1,180	990	990	911	911	990	990

Table 6 reports our results, replicating those in Table 3 but now using instrumental variables estimation techniques. In 11 of the 12 alternative specifications, IT intensity remains positively significantly related to firm performance heterogeneity. Overall, these results are consistent with direct causality, that is, industry IT intensity "causing" firm-specific performance heterogeneity.

Table 7 partitions the sample into young and old firms, as in Table 5, but now runs instrumental variable regressions, as in Table 6. Table 5 results hold up well in regressions of firm-specific stock return heterogeneity, with IT intensity attracting positive, significant coefficients in five of the six alternative specifications for both young and old firms. The sales growth heterogeneity regressions are weaker, with IT intensity retaining significance in four of the six specifications for young firms and three of the six for old firms. Note however, that the rough magnitudes of the point estimates are broadly similar across comparable specifications in Tables 5 and 6. As with the Table 5 regressions, an alternative partition at *age* = 10 years generates qualitatively similar results for stock return heterogeneity in both subsamples, but generates stronger results for sales growth heterogeneity using young firms. In contrast, partitioning at *age* = 5 years renders IT intensity significant in only two IV sales growth heterogeneity specifications for young firms, but in three for old firms, and in only four IV stock return heterogeneity specifications for young firms, but in all six for old firms.

We conclude that causality runs from stepped-up IT intensity to magnified firm-specific performance heterogeneity in both young and old firms, but this is more certain if heterogeneity is measured using stock returns than using sales growth.

Table 8 reexamines the impact of firm performance heterogeneity on TFP growth using our tax rate and marginal cost estimates as instruments for the component

Table 7

Two-stage panel regressions of firm-specific performance heterogeneity on IT intensity and controls, with time and industry fixed effects, estimated separately for young and old firm subsamples

Dependent variables are industry-level measures of firm-specific heterogeneity in stock returns or sales growth rates. Within each set, the first four columns have absolute firm-specific variation $\ln(\sigma_\varepsilon{}^2)$ as their dependent variables; while the last two columns use relative firm-specific variation, $\ln(\sigma_\varepsilon{}^2)-\ln(\sigma_m{}^2)$, where $\ln(\sigma_m{}^2)$ is absolute systematic variation. IT intensity, defined as IT capital assets (computers and software) over other capital assets, is estimated in a first-stage regression with *IT tax rates* and the *marginal cost of IT (quality) production* as instrumental variables. The control variables are as follows: *Age* is the average age of firms in an industry, defined as years listed in CRSP. *Size* is the average market capitalization or sales of the firms in each industry in the returns and sales growth heterogeneity regressions, respectively. The *Herfindahl* index is sales-based. *R&D* is estimated R&D capital stock over PP&E. *Leverage* is short plus long-term debt over total assets. *Liquidity* is current assets over current liabilities. Stock return variation is estimated using 12 monthly observations each year. Real sales growth variation is constructed using 12 quarterly observations over three-year rolling windows. In constructing variation measures, firms with fewer than 12 observations are excluded. IT intensity and controls are lagged by one year for returns variation regressions, and averaged over lagged three-year windows for sales growth variation regressions. All regressions include time and industry fixed effects. Observations are weighted by lagged total assets in the returns variation regressions and average industry total assets over lagged three-year windows for sales growth variation regressions. The sample period is 1971–2000. The sample excludes IT-producing industries, finance industries (SIC 6000 to 6999), industries with fewer than five firms, and industries whose IT capital is ill defined. Numbers in parentheses are probability levels for rejecting the null hypothesis of a zero coefficient, based on *t*-statistics adjusted for industry clustering to eliminate bias due to serial dependence within industries. Asterisks denote significance at 10% or better.

Panel A reports regression results for a young firm subsample, which contains firms younger than the median age of eight years as a listed firm in CRSP. Panel B reports regression results for an old firm subsample, which contains firms that have been listed in CRSP for eight years or more.

Panel A. New firm subsample

	Stock returns						Sales growth					
	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Abs. firm-specific	Rel. firm-specific	Rel. firm-specific
Information technology												
ln(*IT*)	0.685*	0.593*	0.582*	0.528*	0.100*	0.065	0.652*	0.267	0.316*	0.284	0.205*	0.318*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.064)	(0.136)	(0.000)	(0.211)	(0.006)	(0.156)	(0.014)	(0.008)
Corporate demography												
ln(*Age*)		0.077		0.119		−0.214*		−1.089*		−0.842*		0.281
		(0.743)		(0.597)		(0.081)		(0.046)		(0.048)		(0.436)
ln(*Size*)		−0.258*		−0.210*		−0.189*		−0.396		−0.300		0.133
		(0.055)		(0.079)		(0.009)		(0.179)		(0.199)		(0.312)
Competition												
Herfindahl		−0.208		−0.151		0.997*		3.428		2.406		0.013
		(0.812)		(0.859)		(0.007)		(0.392)		(0.496)		(0.994)
Technology												
ln(1+*R&D*)		−1.032		−0.167		−0.786*		−0.074		1.560*		0.270
		(0.116)		(0.761)		(0.005)		(0.944)		(0.051)		(0.760)
Financing												
Leverage		−0.980*		−0.777*		−0.472*		−1.708		−0.753		−1.286*
		(0.084)		(0.100)		(0.064)		(0.138)		(0.417)		(0.097)
Liquidity		0.239		0.235		0.019		0.346		−0.209		−0.433
		(0.329)		(0.294)		(0.822)		(0.307)		(0.518)		(0.157)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Systematic variation												
Absolute systematic			0.116	0.095					0.147*	0.106*		
			(0.165)	(0.147)					(0.015)	(0.016)		
Adjusted R^2	0.605	0.649	0.602	0.628	0.528	0.540	0.675	0.709	0.690	0.709	0.388	0.383
Sample size	1,055	1,055	1,025	1,025	1,055	1,055	775	775	691	691	775	775
Panel B. Old firm subsample												
Information technology												
ln(*IT*)	0.211*	0.102	0.201*	0.128*	0.145*	0.122*	0.317*	0.081	0.292	0.181	0.315*	0.334*
	(0.002)	(0.113)	(0.000)	(0.014)	(0.050)	(0.014)	(0.049)	(0.680)	(0.184)	(0.328)	(0.007)	(0.015)
Corporate demography												
ln(*Age*)		−0.352		−0.275		0.021		−0.588		−0.522		−0.157
		(0.246)		(0.258)		(0.853)		(0.253)		(0.179)		(0.559)
ln(*Size*)		−0.240*		−0.248*		−0.219*		−0.276		−0.148		0.150
		(0.028)		(0.004)		(0.000)		(0.334)		(0.572)		(0.215)
Competition												
Herfindahl		−0.981*		−0.436		1.021*		−4.042*		−5.928*		0.249
		(0.080)		(0.365)		(0.009)		(0.000)		(0.000)		(0.725)
Technology												
ln(1+*R&D*)		1.302*		1.334*		−0.963*		−0.246		2.059*		−0.046
		(0.007)		(0.004)		(0.001)		(0.834)		(0.038)		(0.953)
Financing												
Leverage		−1.070*		−0.615		0.061		−3.709*		−3.045*		−1.328*
		(0.092)		(0.181)		(0.824)		(0.020)		(0.015)		(0.061)
Liquidity		0.285		0.276*		0.111		−0.302		−0.476		−0.282
		(0.150)		(0.077)		(0.125)		(0.509)		(0.179)		(0.432)
Systematic variation												
Absolute systematic			0.313*	0.226*					0.162*	0.088		
			(0.000)	(0.000)					(0.077)	(0.143)		
Adjusted R^2	0.774	0.811	0.797	0.819	0.655	0.672	0.479	0.537	0.482	0.555	0.350	0.350
Sample size	1,100	1,100	1,066	1,066	1,100	1,100	931	931	851	851	931	931

Table 8

Two-stage panel regressions of TFP growth on firm-specific performance heterogeneity and controls, with time and industry fixed effects

Panel data are U.S. industries followed from 1971–2000, across six non-overlapping five-year intervals (1971–1975, ..., 1996–2000). The dependent variable is industry TFP growth rate during each five-year interval. Initial TFP is measured at the beginning year at each interval. Performance heterogeneity measures are the average of values over the prior five-year interval, ($t-9$, $t-5$). All regressions include time and industry fixed effects. Observations are weighted by the industry's total assets, averaged over the prior window. The sample excludes IT-producing industries, finance industries (SIC 6000 to 6999), and industries with fewer than five firms available for constructing TFP growth rates or performance heterogeneity measures, as well industries whose IT capital is ill defined. Columns 8.1 and 8.2 use BEA industry-level TFP data while columns 8.3 and 8.4 use TFP measures constructed from Compustat sample firms. All columns report 2SLS regressions results with *IT tax rates* and the *marginal cost of IT* (*quality*) *production* used as instruments. Numbers in parentheses are probability levels, based on *t*-statistics adjusted for industry clustering. Asterisks denote significance at 10% or better.

	TFP growth defined using BEA industry-level data		TFP growth defined using Compustat sample firms	
	8.1	8.2	8.3	8.4
Performance heterogeneity				
Absolute firm-specific returns variation, $\ln(\sigma_\varepsilon^2)$	0.299*		1.130*	
	(0.098)		(0.000)	
Absolute systematic returns variation, $\ln(\sigma_m^2)$	−0.206		−0.822*	
	(0.340)		(0.012)	
Relative firm-specific returns variation, $\ln(\sigma_\varepsilon^2)-\ln(\sigma_m^2)$		0.383*		1.264*
		(0.033)		(0.000)
Controls				
Initial ln(*TFP*)	−0.180	−0.174	−0.391*	−0.340*
	(0.288)	(0.280)	(0.000)	(0.000)
Adjusted R^2	0.623	0.613	0.749	0.715
Sample size	190	190	190	190

of the former associated with exogenous changes in IT. Note that to avoid collinearity, we cannot include instrumented IT intensity in these regressions. As in the previous round of estimates, firm performance heterogeneity remains significantly positively related to both measures of TFP growth.

4.2. The robustness of our performance heterogeneity regressions

4.2.1. Alternative variables

4.2.1.1. Previously used proxies for creative destruction. To confirm that our results reflect creative destruction, we consider alternative dependent variables previously used to gauge that process. Using country-level data, Fogel, Morck, and Yeung (2008) show that faster turnover in a country's list of top firms, which they use to proxy for creative destruction, correlates with faster *per capita* GDP and productivity growth. Comin and Philippon (2005) use conceptually analogous measures for U.S. industries from *Compustat* data. Following their approach, we define three turnover rates of leading firms in industry *i* in year *t* as the probabilities of a firm falling out of its industry's top quintile within five years, with top quintiles defined by each of market value, operating income, and sales. We then generate an analog to Table 3, but with these turnover measures, rather than firm-specific performance heterogeneity, as dependent variables. The results, shown in Table 9, are qualitatively similar to those in Table 3—IT intensity remains positive and significant across all specifications, while the other controls (except *size*) have insignificant and inconsistent signs.

4.2.1.2. Alternative ways of estimating firm performance heterogeneity measure. As further robustness checks, we consider alternative constructions of sales firm-specific performance heterogeneity measures constructed with five-year, rather than three-year, windows and with non-overlapping, rather than overlapping, three-year windows (i.e., dropping two of every three years). All generate qualitatively similar results, except for reduced significance levels if the dependent variable is relative firm-specific sales growth heterogeneity constructed using five-year windows.

We require complete data for a firm to be included in estimating the firm-specific performance heterogeneity of its industry. Repeating our tests including firms with one, two, or three missing observations generates qualitatively similar results to those shown. We drop firm-quarter observations with Compustat footnotes. Retaining them generates qualitatively similar results. In estimating sales growth heterogeneity, we scale by the average of current and lagged sales in (3). Using the earlier period's sales as the denominator yields qualitatively similar results.

Extreme values may affect our heterogeneity estimates. Rerunning (4) using data winsorized at the 1% level does not qualitatively change our results. Neither does winsorizing the firm performance heterogeneity measures directly.

Table 3 uses variables constructed using value-weighted industry and market indexes in regression (4). Equal-weighted indexes generate qualitatively similar results in regressions with absolute firm performance heterogeneity as dependent variables. When relative firm performance heterogeneity measures are used as dependent variables, results are weaker, perhaps again reflecting an overly restrictive specification of (12) when compared with (13), rather than genuine economic insignificance.

Table 9
Panel regressions of turnover measure on IT intensity and controls with time and industry fixed effects

The dependent variable is turnover rate based on market value, operating income, and sales. Turnover rate is the probability of a firm dropping out of the industry's top quintile within five years, as defined in Comin and Philippon (2005). All regressions include time and industry fixed effects. Observations are weighted by lagged total assets. Columns 9.2, 9.4, and 9.6 report 2SLS regressions results with *IT tax rates* and the *marginal cost of IT (quality) production* used as instruments. The sample period is 1971–2000. The sample also excludes IT-producing industries, finance industries (SIC 6000 to 6999), industries with fewer than five firms, and industries whose IT capital is ill defined. Numbers in parentheses are probability levels, based on *t*-statistics adjusted for industry clustering to eliminate bias due to serial dependence within industries, at which the null hypothesis of a zero coefficient can be rejected. Asterisks denote significance at 10% or better.

	Market value		Operating income		Sales	
	9.1	9.2	9.3	9.4	9.5	9.6
Information technology						
ln(*IT*)	0.029*	0.051*	0.032*	0.036*	0.021*	0.035*
	(0.033)	(0.009)	(0.000)	(0.040)	(0.012)	(0.009)
Corporate demography						
ln(*Age*)	0.035	0.046	−0.053	−0.051	0.076*	0.083*
	(0.593)	(0.481)	(0.231)	(0.278)	(0.041)	(0.026)
ln(*Size*)	−0.099*	−0.101*	−0.057*	−0.057*	−0.129*	−0.124*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Competition						
Herfindahl	−0.077	−0.110	0.022	0.016	−0.076	−0.104
	(0.690)	(0.541)	(0.871)	(0.910)	(0.496)	(0.387)
Technology						
ln(1+*R&D*)	−0.230	−0.262	−0.011	−0.017	−0.104	−0.120
	(0.151)	(0.119)	(0.938)	(0.914)	(0.621)	(0.581)
Financing						
Leverage	−0.020	0.005	0.119	0.124	0.178*	0.194*
	(0.920)	(0.981)	(0.466)	(0.466)	(0.056)	(0.038)
Liquidity	−0.045	−0.063	−0.025	−0.028	0.007	-0.005
	(0.493)	(0.378)	(0.291)	(0.313)	(0.830)	(0.891)
Adjusted R^2	0.535	0.514	0.647	0.634	0.714	0.700
Sample size	1,180	1,180	1,180	1,180	1,010	1,010

4.2.1.3. Alternative estimates of IT intensity. Furthermore, we check the robustness of the construction of IT intensity. We use Törnqvist indexes to aggregate IT assets deflated by BEA hedonic prices (BEA, 1998). Alternative indexes without adjustments for inflation generate qualitatively similar results.

4.2.1.4. Alternative constructions of other variables. 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.[19] 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 ($\rho = 0.49$, $p < 0.01$) 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. Although this has solid economic justification, R&D spending is nonetheless often used as a proxy for R&D capital stock—see, e.g., Morck, Shleifer, and Vishny (1988). Using simple current or lagged R&D spending over assets generates qualitatively similar results to those shown.

4.2.2. Alternative econometric approaches

The regressions in Table 3 weight observations by industry total assets. Weighting instead by industry market capitalization or industry sales generates qualitatively similar results. So do equally weighted regressions for stock return heterogeneity and for sales growth heterogeneity if we drop industries with weights below 0.5% of the sample total. Using fixed weights, average assets for 1966 through 1970 also generates qualitatively similar results.

Fig. 5 presents scatter plots of $\ln(\sigma_\varepsilon^2)$ for stock returns and sales growth against IT intensity. These show broad-based positive correlations that are 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 and MacBeth (1973) regressions by appending the method of Newey and West (1987). Petersen (2005) shows that serial correlations can generate inflated *t*-statistics even with this correction. Still, the method is widely used and may have other advantages. In fact, modified Fama-MacBeth regressions yield stronger results than those shown in regression tables of the paper.

4.2.3. Additional control variables

We repeat our performance heterogeneity multiple regressions supplemented with various additional controls. None of the control changes the results qualitatively.

We control for average firm size in each industry. As a robustness check, we also consider the distribution of firm size for each industry. Using the standard deviation of the logarithms of firm market capitalization, sales, or total assets to control for 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 industry advertising expenses over property, plant, and equipment (PP&E) (Compustat item 45 over item 8) as an additional control. 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

[19] Listing dates can yield problematic measures of age for a number of reasons (Jovanovic and Rousseau, 2001; Fink, Fink, Grullon, and Weston, 2005; Philippon and Sannikov, 2007). Fink, Fink, Grullon, and Weston (2005), gauging age as years since incorporation, find that age explains most of the long-run trend in firm-level volatility. However, our study is not designed to explain the magnitudes of this trend. We include time fixed effects throughout so our tests circumvent such issues. See Philippon and Sannikov (2007) for further explanation.

products of 25 and 199). Including either or both of these variables does not qualitatively change our results.

Investment in conventional capital assets might conceivably increase firm performance heterogeneity by increasing uncertainty about a firm's future cash flows. We therefore control for non-IT capital investment (industry aggregate non-IT investment over industry aggregate non-IT capital, as defined in Section 2.1). Qualitatively similar results obtain.

Irvine and Pontiff (2004) consider import penetration, which is only available for manufacturing industries. If we include import penetration as an added control, the IT variable remains significant, except for regressions of relative firm-specific performance heterogeneity. However, in these regressions, both IT and import penetration become insignificant, perhaps reflecting the smaller sample ($n = 19$). Import penetration exhibits little time variation, and so may be collinear with industry fixed effects.

Firms with operations in more industries, all else equal, track the market more closely and their primary industry indexes 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, Bharath, and Viswanathan (2004) argue that diversification raises investor uncertainty and increases stock return variation and Morck, Shleifer, and Vishny (1989) argue that investors view diversification per se as evidence of firm-specific governance problems. We gauge average firm diversification by the number of two-digit industries in which the firm reports positive sales, and average this for each industry-year. Compustat's 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. Controlling for diversification leaves IT intensity with significant coefficients similar to those in Table 3 in regressions of absolute firm-specific variation measure of sales growth, but insignificant in the other specifications. The less robust significance could reflect the shorter panel, rather than genuine economic insignificance. There is little variation in industry average diversification over time, and dropping industry fixed effects again restores the full pattern of signs and significance for IT intensity in the tables.

Multinational firms are subject to shocks, like currency fluctuations and foreign demand fluctuations, which 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. These data yield the same pattern of results as industry diversification and are subject to the same limitations.

4.3. The robustness of our productivity regressions

Recall that BEA industry TFP growth and TFP growth estimated from Compustat generate largely qualitatively similar results, described in Section 3.3. Including unlisted firms, as in the BEA figures, does not affect our results.

Our TFP growth results survive several additional robustness checks.

To avoid any possible correlation between our regression weights and error terms, we reestimate our results using out-of-sample weights, 1966–1970 average assets, in all time periods and observe qualitatively similar results. In equally weighted regressions, firm performance heterogeneity is significant only if initial TFP levels are also included—even in regressions excluding industries with weights below 0.5% of the sample total. This might indicate noisier TFP growth or performance heterogeneity estimates for smaller industries, or perhaps more vigorous creative destruction in larger industries. Since growth in larger industries is ostensibly most economically important, even the latter preserves the economic significance of our results.

Five-year periods might be too short to capture the full impact on TFP of creative destruction associated with IT capital. To examine the effect of creative destruction in a longer horizon, we run a cross-section regression of 30-year industry TFP growth on firm performance heterogeneity, averaged across the same years, and controls. This yields the same pattern of signs and significance as Table 4.

Another issue is the window length used for the regressor variable—firm performance heterogeneity. Table 4 uses the average across the five years prior to the beginning of the five-year window over which the regressand, TFP growth, is estimated. Repeating the exercise using stock return heterogeneity measured instead over a one- or three-year period prior to the TFP growth estimation window attracts coefficients roughly one-fifth and three-fifths, respectively, as large as those in Table 4, though p-levels fall short of statistical significance in specifications without initial TFP.

5. Conclusions

Elevated firm performance heterogeneity—cross-sectional firm-specific variation in individual firms' stock returns and real sales growth—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 the 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 view, 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:

1. *Creative destruction is more intense in higher income countries*: Stocks in countries with higher incomes

(Morck, Yeung, and Yu, 2000) or faster economic growth (Durnev, Li, Morck, and Yeung, 2004) exhibit higher firm-specific return variation. If this reflects more intense creative destruction, these findings support Aghion, Howitt, and Mayer-Foulkes' (2005) theoretical prediction of more creative destruction in higher income countries, and factor accumulation in lower income countries. They also more generally support the theories of Schumpeter (1912) and their formalizations by Aghion and Howitt (1992, 1998), Aghion, Angeletos, Banerjee, and Manova (2004), Aghion, Howitt, and Mayer-Foulkes (2005), Acemoglu (2005) and Acemoglu, Aghion, and Zilibotti (2006), who 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, Yeung, and Yu (2000) link greater firm-specific performance heterogeneity to the quality of government, by which they mean an absence of corruption, an efficient judiciary, and a general respect for the rule of law. La Porta, Lopez-de-Silanes, and Shleifer (1999) argue that governments that provide these institutional public goods are protecting private property rights. La Porta, Lopez-de-Silanes, and Shleifer (2006) show effective private property rights protection to be a necessary condition for financial development. These support Baumol (1990), Murphy, Shleifer, and Vishny (1991), Gans, Hsu, and Stern (2002), and others who argue that sound private property rights are a pre-condition for creative destruction.
3. *Creative destruction is more intense if corporations are more transparent*: La Porta, Lopez-de-Silanes, and Shleifer (2006) argue that corporate transparency is critical to making investors' de jure protection effective. Morck, Yeung, and Yu (2000), Bris, Goetzmann, and Zhu (2004), Durnev, Li, Morck, and Yeung (2004), Fox, Morck, Yeung, and Durnev (2003), Huang (2004), Ozoguz (2004), and Jin and Myers (2006) 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 more secure and cheaper.
4. *Creative destruction is more intense if financial systems are more developed*: Schumpeter (1912) argues that entrepreneurs are often penurious, and so need financing to develop their innovations. He therefore argues that a well-developed financial system is a prerequisite for growth through creative destruction. Consistent with this, King and Levine (1993) show financial development to be of first-order importance to economic growth. Wurgler (2000) links greater firm-specific performance heterogeneity to financial development. Bris, Goetzmann, and Zhu (2004) and Durnev, Li, Morck, and Yeung (2004) find higher firm-specific stock return variation in more financially developed countries. Durnev, Li, Morck, and Yeung (2004) also report higher TFP growth in countries with elevated firm-specific stock return variation. Davis, Haltiwanger, Jarmin, and Miranda (2006) report that the increase in firm-level volatility found by Morck, Yeung, and Yu (2000), Campbell, Lettau, Malkiel, and Xu (2001), and others in U.S. stocks is evident only in listed firms. This accords with Schumpeter's (1912) argument that creative destruction requires external financing, and suggests that public equity financing might be especially important.
   Given these linkages, the findings of Morck, Yeung, and Yu (2000) and Jin and Myers (2006) can be reinterpreted as indirectly supporting the importance of financial development to creative destruction.
5. *Creative destruction is more intense in more financially open economies*: Li, Morck, Yang, and Yeung (2004) show that firm-specific stock return variation rises in emerging economies after they open to international portfolio investment. Caves (1982) and others argue that openness encourages technology transfer, so the effect Li, Morck, Yang, and Yeung (2004) observe could partially reflect creative destruction associated with the new technology.
6. *Creative destruction need not destabilize the macroeconomy*: Durnev, Li, Morck, and Yeung (2004) 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.[20] The two results are not mutually exclusive because firm-specific 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 in macroeconomic growth.[21]

Our thesis that elevated firm performance heterogeneity signals intensified creative destruction in no way excludes other explanations of firm-specific performance variation. Philippon (2003), Irvine and Pontiff (2004), and Gaspar and Massa (2006) emphasize increased competition, and Schumpeter (1939) posits that waves of creative destruction induce subsequent waves of price competition. Pastor and Veronesi (2003), Fama and French (2004), Fink, Fink, Grullon, and Weston (2005), Bennett and Sias (2006), Davis, Haltiwanger, Jarmin, and Miranda (2006), and Brown and Kapadia (2007) link rising firm-specific stock return variation to the growing importance of smaller, younger firms. This also dovetails with our thesis, for Schumpeter (1912) argues that new, initially small firms are the carriers of new technology and the harbingers of creative destruction. We believe that our thesis underscores the importance of these findings and

[20] Ramey and Ramey (1995) interpret their finding as decreased uncertainty spurring investment, as in Pindyck (1991).

[21] Comin and Mulani (2005) model firm-specific risk rising and systematic risk falling as firms shift their R&D towards inimitable innovations and away from imitable ones, and argue that such a shift occurred in the U.S. in recent decades. This is consistent with GPT applications being hard to imitate initially, when their contribution to TFP growth is greatest, as in Schumpeter (1939).

other findings regarding firm-specific performance heterogeneity by providing a unifying framework for this emerging literature. This need not, of course, preclude other partial explanations, and we welcome further work in this area.

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