VARYING HETEROGENEITY AMONG U.S. FIRMS: FACTS AND IMPLICATIONS

Hyunbae Chun, Jung-Wook Kim, and Randall Morck*

Abstract—U.S. firms' stock return volatility rose fivefold from 1971 through 2000 and then reverted to near 1971 levels by 2006. This was driven mainly by a rise and fall in the firm-specific, rather than systematic, component of volatility. Firm-level total factor productivity growth volatility exhibited a similar pattern. We hypothesize that firm heterogeneity, reflected in firm-specific volatility, rises as a new general purpose technology (GPT) propagates across the economy and then ebbs once the GPT is widespread. Measuring GPT adoption by information technology capital intensity, we find robust cross-industry empirical evidence supporting the hypothesis.

I. Introduction

IN the latter twentieth century, heterogeneity among listed U.S. firms, as gauged by firm-specific volatility in stock returns, profits, and real sales growth, increased substantially (Morck, Yeung, & Yu, 2000; Campbell et al., 2001; Comin & Philippon, 2005; Comin & Mulani, 2006; Wei & Zhang, 2006; Chun et al., 2008).[1] We find that this reversed in the early twenty-first century, with firm-specific stock return volatilities decreasing to early 1970s levels by 2006 and other volatility measures subsiding more slowly.

We propose that this pattern captures stages in the propagation of information technology (IT), a general purpose technology (GPT), through the economy. A GPT is a technology that, like the steam engine in the early industrial revolution and electrification in the early twentieth century, induces process and product innovations across most industries, ultimately enhancing long-run productivity and economic growth (Bresnahan & Trajtenberg, 1995; Helpman & Trajtenberg, 1998; Jovanovic & Rousseau, 2005).[2]

When a new technology is introduced into an economy, the potential productivity gains and costs of its efficient use are uncertain. Recent insightful models analyze this using stock return volatility. For example, Pastor and Veronesi (2009) show how uncertainty regarding the productivity of new technology affects the volatility as well as the level of stock price. Comin, Gertler, and Santacreu (2009) examine a model where firms' salable rights over future technologies elevate asset price volatility. Our working hypothesis, based on Schumpeter's (1912) creative destruction, explores further the ideas in these models by focusing on dynamics at the level of individual firms with heterogeneous abilities to adopt a new GPT (Schumpeter, 1912; Hayek, 1941; Hobijn & Jovanovic, 2001; Bresnahan, Brynjolfsson, & Hitt, 2002).

Adopters of a new GPT must sort out its most efficient applications, and these are likely to be clearer in some settings than in others. Unlike previous recent studies, we posit that a GPT may propagate across firms and industries at uneven speeds, with successful early adopters accumulating quasi-rents and outpacing unsuccessful adopters and nonadopters, as in Schumpeter (1912). This necessarily, ceteris paribus, renders firm performance more heterogeneous than in periods without technology shocks.

Once successful innovators have ascertained the best uses of a new GPT, other firms should eventually imitate them. This implies a postadoption period of eroding innovator quasirents and declining firm performance heterogeneity. This pattern of an important innovation inducing a period of creative destruction followed by a period of consolidation, first proposed by Schumpeter (1939) as an explanation for business cycles, thus predicts a low-frequency volatility cycle.

To explore this hypothesis, we decompose firm-level volatilities in stock returns and in the growth rates of output, total factor productivity (TFP), labor, and capital into two components: a systematic (correlated with economy or industry shocks) component and a firm-specific (residual or idiosyncratic) component. We average the firm-specific component of each variable across all firms in an industry over a given time window to characterize that industry's firm heterogeneity. This industry-level panel lets us explore shifting heterogeneity both within and across industries.

We find firm-level stock return volatility, constructed using monthly total stock return data for each year, rising more than fivefold from 1971 to 2000 and then dropping back even more dramatically, reverting by the end of 2006 to levels found in the first years of our sample period. Output volatility exhibits a similar pattern, though less dramatic—probably because this variable is constructed across ten-year overlapping windows using annual growth rates rather than the nonoverlapping annual windows used for

Received for publication April 27, 2008. Revision accepted for publication March 4, 2010.

* Chun: Sogang University; Kim: Seoul National University; Morck: University of Albert.

We thank David Cook, Joonkyung Ha, Stewart Myers, Jungsoo Park, Andrei Shleifer, Jeremy Stein, Bernard Yeung, and participants at the Globalization, Firm Dynamics and Economic Growth Conference in Tokyo, Hallym University, Hong Kong Polytechnic University, the Korea Academic Society of Industrial Organization, Korea University, Seoul National University, SUPEX International Conference on Globalization and Growth, the Western Economic Association, and Yonsei University. We are also most grateful to the editor and two anonymous referees for particularly helpful comments. We gratefully acknowledge partial financial support from the KB Research Institute and the Sogang University Research Fund, the SAS Research Fund of the University of Alberta and the Institute of Management Research at Seoul National University, and the SSHRC.

[1] Similar increases are evident in other countries (Li et al., 2004; Thesmar & Thoenig, 2004; Jin & Myers, 2006; Parker, 2006). Unlisted U.S. firms do not share this pattern (Davis et al., 2006). However, listed firms in the United States account for half of aggregate value-added and 95% of private R&D (Comin & Mulani, 2007). Thus, the causes and consequences of this qualitative change merit investigation.

[2] Bresnahan and Trajtenberg (1995) and Jovanovic and Rousseau (2005) characterize a GPT as (a) having profitable applications in all, or almost all, industries; (b) raising revenues and lowering costs over time to successful adopters; and (c) stimulating investment in, and production of, new products or processes.

The Review of Economics and Statistics, August 2011, 93(3): 1034–1052

stock return volatilities. Both firm-level volatility measures rise and abate primarily because their firm-specific components rise and abate relative to their systematic components. This suggests qualitatively changing shocks to listed U.S. firms. In the final decades of the twentieth century, shocks to individual firms eclipsed shocks to whole industries or the whole economy. This pattern reversed in the first decade of the new century, with economy-wide and industry shocks reasserting their earlier importance and firm-specific shocks fading back to their earlier levels. This implies that winners and losers became more sharply distinguished within each industry in the late twentieth century and that these differences have eroded early in the new century.

We also find shifting TFP growth rate volatility to be the most important driver of output growth rate volatility. This too is consistent with an underlying role for technological innovation: creative innovators became uniquely productive while destroying the productivities of their more staid competitors, elevating firm-specific TFP growth rate volatility in the late twentieth century.

We employ an industry-year panel to test our hypotheses, against explanations advanced elsewhere for shifting firm-level volatilities: intensified competition from deregulation and globalization (Philippon, 2003; Gaspar & Massa, 2006; Irvine & Pontiff, 2009), smaller and younger listed firms (Fama & French, 2004; Fink et al., 2005; Bennett & Sias, 2006; Davis et al., 2006), enhanced investor protection and transparency (Morck et al., 2000; Jin & Myers, 2006), research and development (Comin & Mulani, 2007), and information technology (Chun et al., 2008). Evidence supports each explanation, but mostly using late-twentieth-century data, a period of rising firm-level volatility. By reconsidering these explanations in periods of both rising and falling firm-level volatility, we can further explore their roles.

Our industry panel regressions leave only information technology consistently significant and with stable coefficients throughout the rise, abatement, and changing decomposition of firm-level output growth rate and stock return volatilities. Thus, even as firm heterogeneity is first amplified and then attenuated at successive stages in the diffusion of IT, the cross-sectional relationship between IT and firm heterogeneity remains stable. This is consistent with firm heterogeneity across industries primarily reflecting differing intensity of IT investment during both periods. These results survive an exhaustive series of robustness checks, including an instrumental variable (IV) specification designed to deal with possible endogeneity issues.

Based on these findings, we propose that creative destruction, initiated by the arrival of a new GPT, underlies a sequence of structural changes that the U.S. economy has experienced in recent decades. At first, the GPT magnifies firm heterogeneity as successful innovators, many young upstart firms, earn quasi-rents. Subsequently, as the best uses of the new GPT propagate widely, these quasi-rents abate and firms become more homogeneous again. These results in no way invalidate the other explanations of firm-level volatility listed above, but rather suggest they may be part of a broader pattern: a low-frequency cycle in firm-level volatility and its decomposition, evident in both time-series and cross-sectional data, that tracks stages in the propagation of a new GPT.

This paper is structured as follows. Section II explains our data and variables. Section III describes our firm volatility measures and their decomposition. Section IV examines possible determinants of firm-specific stock return and TFP growth volatilities. Section V discusses robustness of results, and section VI summarizes our conclusions and their implications.

II. Data and Variables

A. *Stock Returns and Growth Rates in Output, TFP, and Inputs*

To measure stock return volatility for a year, we use monthly CRSP total stock returns. However, firms' output, TFP, labor, and capital growth rates are available only annually. Their annual volatilities must therefore be inferred from overlapping rolling data windows, which unavoidably induce persistence.

We measure firm output as real value-added, denoted $Y_{j,t}$, with j and t firm and time subscripts, respectively. Real value-added is nominal value-added—operating income before depreciation (Compustat item 13) plus labor and related expenses (item 42)—deflated by the Bureau of Economic Analysis (BEA) gross product originating (GPO) value-added deflator for firm j's two-digit primary industry, $i(j)$. Before 1977, these deflators are unavailable, so we use gross output and intermediate input prices from the Bureau of Labor Statistics (BLS) Multifactor Productivity Database to construct substitutes. Our output growth rate is then

$$g(Y_{j,t}) \equiv ln(Y_{j,t}) - ln(Y_{j,t-1}). \tag{1}$$

A firm's TFP growth rate, $g(TFP_{j,t})$, output growth not accounted for by growth in capital or labor employed, is

$$\begin{aligned} g(TFP_{j,t}) \equiv g(Y_{j,t}) &- \frac{1}{2}(S_{L,j,t} + S_{L,j,t-1})g(L_{j,t}) \\ &- \frac{1}{2}(S_{K,j,t} + S_{K,j,t-1})g(K_{j,t}), \end{aligned} \tag{2}$$

with $S_{L,j,t}$ and $S_{K,j,t}$ the firm's labor and capital cost shares, respectively.[3] $S_{L,j,t}$ is labor and related expenses over this,

[3] TFP growth can reflect technological or other phenomena, such as returns to scale and factor utilization (Hall, 1988; Basu & Fernald, 1997). However, Franco and Philippon (2007) show that firm-level productivity changes are caused mostly by permanent technology shocks rather than transitory and composition shocks. Furthermore, permanent technology shocks, which are almost uncorrelated across firms, explain a large fraction of the firm dynamics but are not relevant for aggregate dynamics. This suggests that changes in macrovolatility, such as the Great Moderation, cannot be recovered from changes in the firm-level volatility without extra assumptions. We are grateful to two anonymous referees for this insight.

plus capital services costs. If labor and related expenses are unreported, we estimate them as industry average wage for $i(j)$, from GPO data, times the firm's workforce (Compustat item 29). If employees' benefits are excluded from labor and related expenses (Compustat footnote 22), we estimate them using the industry-level ratio of benefits to total compensation, from GPO data. Capital services cost is defined as real capital stock, $K_{j,t}$, times industry $i(j)$'s rental price of capital. To estimate the last, we use the BEA fixed reproducible tangible wealth (FRTW) data on the asset composition of each industry each year to aggregate BLS asset-specific rental prices of capital, tax-adjusted as in U.S. Bureau of Labor Statistics (1997), using the Törnqvist method. Firm j's capital cost share, $S_{K,j,t}$, is 1 minus its labor cost share.

Since Compustat includes only listed firms and we exclude financial firms, our aggregates differ from BLS aggregate growth rates. Nonetheless, our average annual TFP growth rates correlate highly with those provided by the BLS ($\rho = 0.57$, p-value $= 0.0003$), despite ours having a somewhat higher mean.

B. *Firm-Level Volatilities and Their Decomposition into Firm-Specific and Systematic Components*

This section describes the construction of our firm-level stock return and fundamentals' (output, TFP, labor, and capital) growth rates volatilities, and their decomposition into firm-specific and systematic components.

We define the stock return total volatility of firm j in year t as the variance of its monthly total (capital gains plus dividends) stock return. We define the total volatilities of firm j's growth rates in output, TFP, labor, and capital to be the variances of these annual growth rates over a ten-year window ending in year t.

We decompose each firm-level total volatility of fundamentals into two components: a systematic (related to industry and economy factors) component and a firm-specific (residual or idiosyncratic) component each year t by running the following OLS regression over the ten-year rolling window ending in year t,

$$g(Y_{j,\tau}) = b_{0,j,t} + b_{1,j,t}\bar{g}_{i(j)}(Y_{j,\tau}) + b_{2,j,t}\bar{g}(Y_{j,\tau}) + u_{j,\tau}, \qquad (3)$$

where $\tau \in [t-9,\ t]$, $\bar{g}_{i(j)}(Y_{j,\tau})$ the value-added-weighted sum of the growth rates of all other firms in the industry, and $\bar{g}(Y_{j,\tau})$ the value-added-weighted sum of the growth rates of all other firms in all industries.[4] The industry and market indexes excluding firm j itself keep large firms from being artificially highly correlated with their industry or market averages. We run separate regressions for each firm in each window, excluding those with fewer than five observations in the window.

We define the systematic output growth volatility of industry i in year t as the sum of squared variations explained by the decomposition regressions (3) for all firms in that industry, $SSM(Y_{j,t})$, normalized by the number of observations, $T_{j,t}$:

$$\sigma^2_{s,i,t}(Y) \equiv \frac{\sum_{j\in i} SSM(Y_{j,t})}{\sum_{j\in i} T_{j,t}}. \qquad (4)$$

We define the firm-specific output growth volatility of industry i in year t as the sum of squared residual variations, $SSR(Y_{j,t})$, analogously normalized by observations

$$\sigma^2_{\varepsilon,i,t}(Y) \equiv \frac{\sum_{j\in i} SSR(Y_{j,t})}{\sum_{j\in i} T_{j,t}}. \qquad (5)$$

An alternative way of expressing this decomposition is as a fraction. We first define industry i's relative firm-specific output growth volatility as a fraction of firm-specific volatility relative to systematic volatility:

$$\psi_{i,t}(Y) \equiv \frac{\sigma^2_{\varepsilon,i,t}(Y)}{\sigma^2_{s,i,t}(Y)}. \qquad (6)$$

We also calculate the fraction of systematic volatility to total volatility for industry i for year t, which we define as ${R_{i,t}}^2(Y)$:

$$R^2_{i,t}(Y) \equiv \frac{\sigma^2_{s,i,t}(Y)}{\sigma^2_{\varepsilon,i,t}(Y) + \sigma^2_{s,i,t}(Y)}. \qquad (7)$$

We analogously define systematic, firm-specific, and relative firm-specific volatilities and R^2 for industry i's TFP, labor, and capital growth rates. Volatility measures and R^2 are also similarly defined for stock returns, but using monthly stock returns and value-weighted industry and market indexes for nonoverlapping one-year windows.

III. Firm-Specific Volatilities

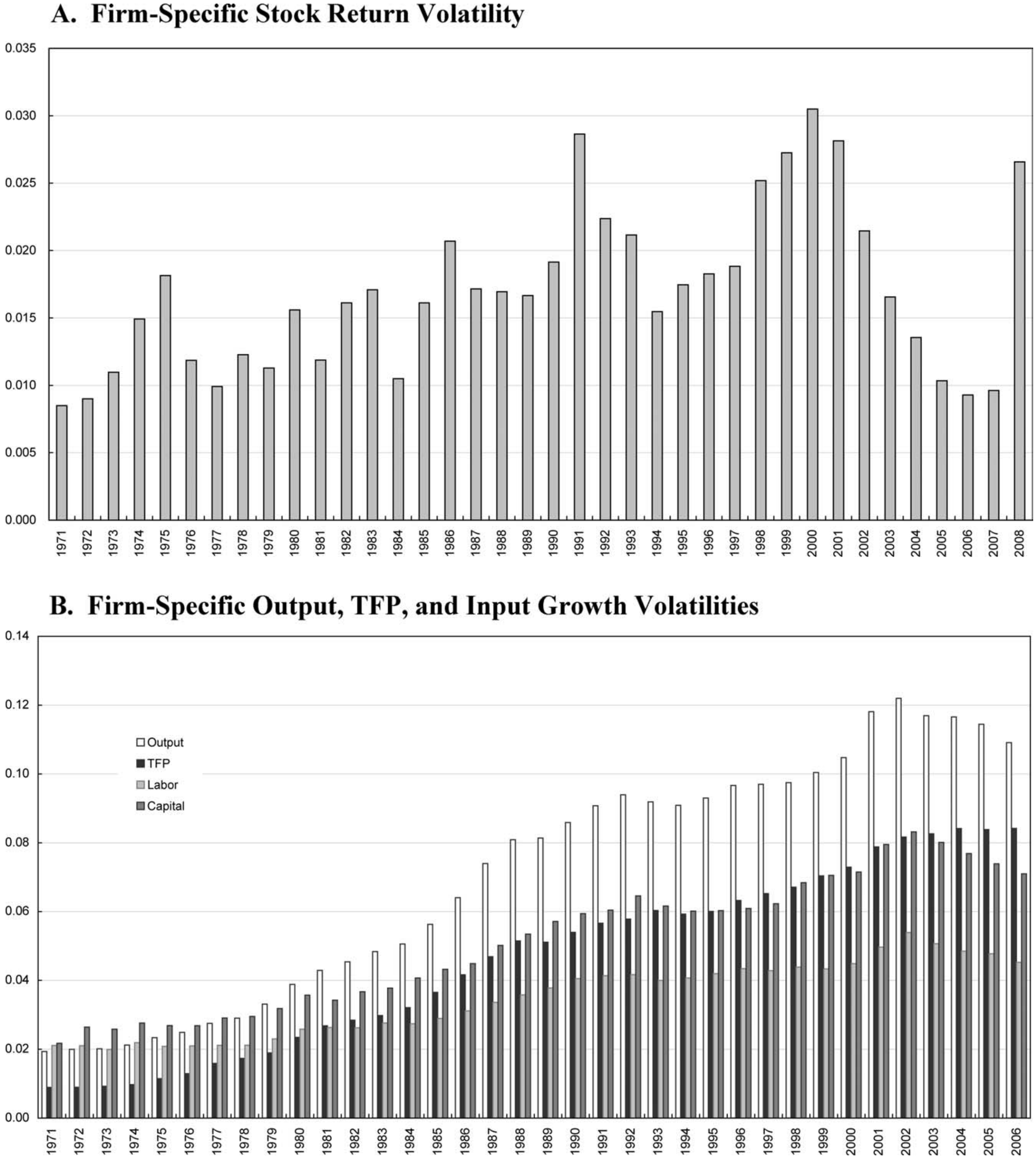
A. *Patterns in the Data*

Figures 1A and 1B graph firm-specific volatilities of stock returns and output, TFP, labor, and capital growth rates each year, averaged across industries and weighted by prior year industry total assets.[5] Firm-level volatilities, equal to the sums of firm-specific and systematic volatilities, exhibit almost identical patterns, indicating that the shifts in firm-level volatilities are primarily due to shifts in firms' idiosyncratic volatilities, not shifts in their exposure to industry or market shocks. All five firm-specific volatilities clearly rise with time until 2000, consistent with Morck

[4] Our two-digit-level industry classification corresponds to that in the GPO and FRTW data sets, designating 55 industries, with 20 in manufacturing. We exclude financial industries (SIC 6000–6999) and industries with fewer than five firms.

[5] Equally weighted data also generate similar patterns.

FIGURE 1.—FIRM-SPECIFIC VOLATILITIES: STOCK RETURNS AND FUNDAMENTALS

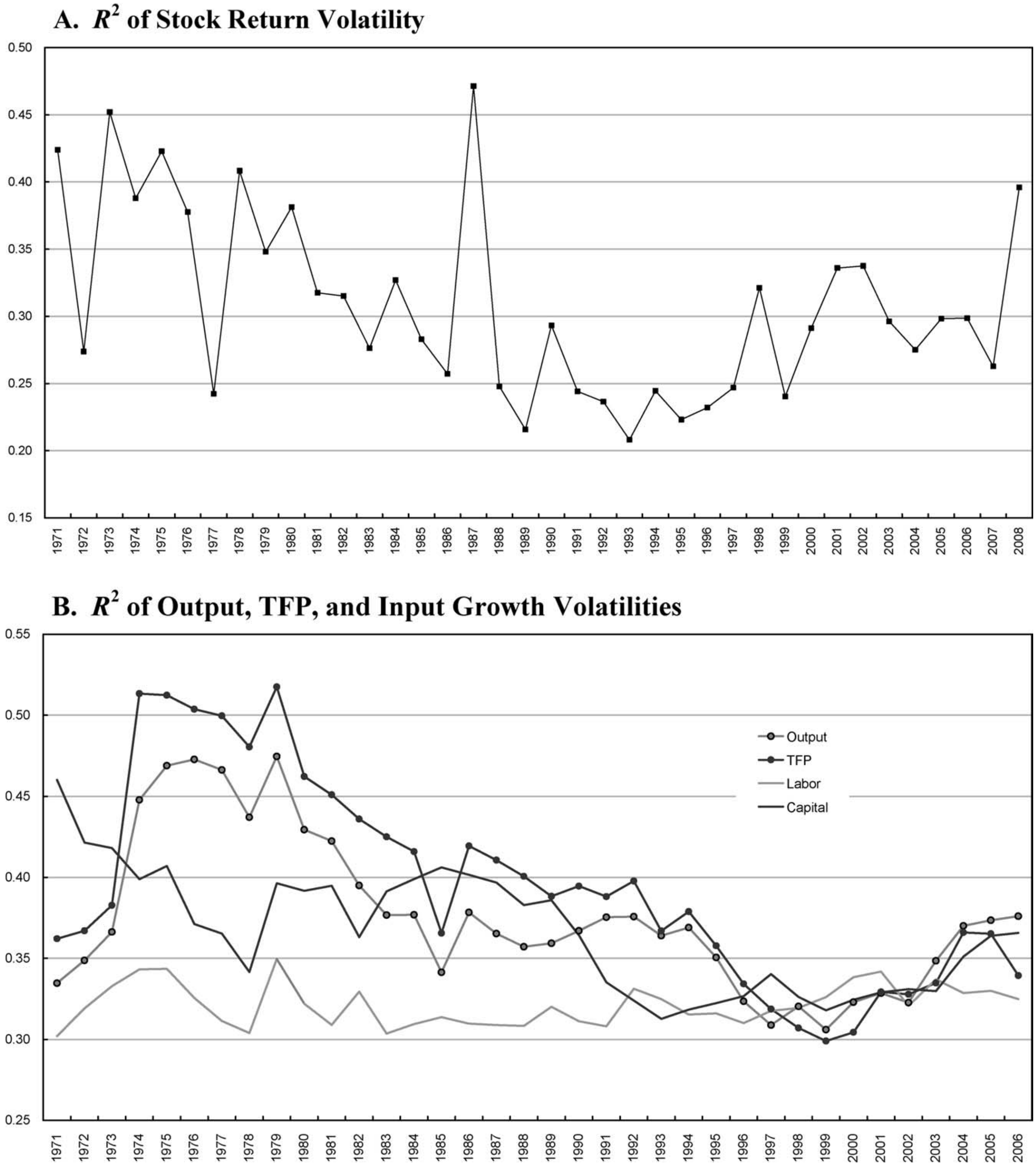


Firm-specific volatility is normalized unexplained variation in equation (3). (A) Firm-specific stock return volatility is estimated using twelve monthly observations per year. (B) Firm-specific output (real value-added), TFP, labor, and capital growth volatilities are estimated using overlapping ten-year rolling windows ending in the designated years. In estimating volatility measures, we dropped firms with fewer than five annual observations for fundamentals in each estimation window. Data graphed are economy averages, weighting industry estimates by prior year industry total asset. Our sample excludes firms in the finance sector (SIC 6000–6999).

et al. (2000) and Campbell et al. (2001) for stock returns and with Comin and Philippon (2005), Comin and Mulani (2006), and Chun et al. (2008) for fundamentals. Thereafter, firm-level stock return volatility subsides markedly, reverting to roughly its 1971 level and then rising abruptly with the panic of 2008. Firm-level fundamentals volatility stops growing around 2001 and then decreases slightly, but does not exhibit the dramatic decrease pattern evident in stock return volatility.[6]

[6] We restrict the sample period to 1971 to 2006 for fundamentals' volatilities due to the limited availability of industry-level value-added deflators and other key data needed for calculating firm-level TFP growth rates.

FIGURE 2.—VOLATILITY DECOMPOSITIONS



For each of stock returns and output, TFP, labor, and capital growth rates, an R^2 is defined as the ratio of systematic volatility (variation related to industry or economy factors) to the firm-level total volatility.

Figures 2A and 2B graph the economy means of the industry-level R^2 measures from equation (7), which express the systematic volatility as a fraction of the total volatility. In every case, firm-specific volatility rises faster than systematic volatility until the mid-1990s, inducing a clear downward trend in the R^2s. Thereafter, systematic volatility becomes steadily more important, inducing an upward trend in the R^2s. Stock returns' R^2 rises by 2008 to levels not seen since the crash of 1987 and not seen for sustained periods since the 1970s.

Together Figures 1 and 2 tell a consistent story. Firm-level volatility rises from 1971 through the turn of the century, primarily because of rising firm-specific volatility. Thereafter, firm-level volatility falls, with firm-specific

TABLE 1.—ANNUALIZED FIRM-SPECIFIC VOLATILITY GROWTH RATES

	Value-Weighted Volatility Growth Rate from			Equal-Weighted Volatility Growth Rate from		
	1970s to 2000s	1970s to 1990s	1990s to 2000s	1970s to 2000s	1970s to 1990s	1990s to 2000s
A. Annualized Long Differences in Firm-Specific Volatility						
Stock returns	1.873*	4.076*	−2.908*	1.046*	2.956*	−2.984*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Output growth	5.540*	6.603*	2.306*	3.748*	5.107*	0.280
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.659)
TFP growth	6.309*	7.153*	3.357*	4.561*	5.992*	0.786
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.348)
Labor growth	3.511*	4.081*	1.668*	2.170*	2.939*	0.197
	(0.000)	(0.004)	(0.040)	(0.000)	(0.000)	(0.725)
Capital growth	4.157*	4.651*	2.338*	3.196*	4.301*	0.346
	(0.003)	(0.010)	(0.006)	(0.000)	(0.000)	(0.595)
B. Annualized Long Differences in Relative Firm-Specific Volatility						
Stock returns	1.133*	3.178*	−3.184*	1.050*	2.850*	−2.760*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Output growth	0.896	1.814*	−0.118	0.904*	1.773*	−1.015*
	(0.122)	(0.092)	(0.357)	(0.011)	(0.000)	(0.048)
TFP growth	1.520*	2.298*	−0.341	1.159*	1.969*	−0.693
	(0.047)	(0.034)	(0.735)	(0.007)	(0.000)	(0.323)
Labor growth	−0.111	0.207	−0.725	0.597*	0.673*	0.325
	(0.772)	(0.605)	(0.219)	(0.023)	(0.047)	(0.665)
Capital growth	0.718	1.684*	−1.358	0.676*	0.893*	0.107
	(0.223)	(0.041)	(0.217)	(0.007)	(0.017)	(0.873)

Stock return volatility is estimated from twelve monthly total return observations each year (firms with fewer than twelve observations are excluded). Other volatility measures are estimated from annual growth rates in ten-year rolling windows ending in the designated year. Firm-specific volatility is residual volatility in firm-level returns or growth rates in a given industry after removing systematic volatility (associated with industry and market factors). Relative firm-specific volatility is residual volatility over systematic volatility. Long-differenced volatility is the period-to-period volatility growth rate, defined as the logarithm of the later period's average volatility minus the logarithm of the earlier period's average volatility, and is annualized and expressed in percentage per year. Periods are decades—the 1970s (1971–1980), 1980s (1981–1990), 1990s (1991–2000), and 2000s (2001–2006)—or pairs of decades, for example, the 1990s and 2000s (1991–2006 inclusive). Value-weighting weights observations by 1970s average industry total assets. The sample is a U.S. industry-year panel excluding the finance sector (SIC 6000–6999). Numbers in parentheses are probability levels at which the null hypothesis of a 0 coefficient is rejected. Asterisks denote significance at 10% or better.

volatility dropping sharply and systematic volatility ebbing more weakly, if at all. The stock return volatilities show an abrupt rise in both components in 2008, with systematic volatility rising far more.

Table 1 shows annualized long differences (Griliches & Hausman, 1986) in each volatility measure across industries, weighting them either by industry total asset or equally. A given volatility measure's long difference is the logarithm of its average across one decade less the logarithm of its average across an earlier decade:

$$\Delta \ln\left[\sigma^2_{\varepsilon,i}(Y)\right] \equiv \ln\left[\bar{\sigma}^2_{\varepsilon,i,t}(Y)\right]_{t\in 2000s} - \ln\left[\bar{\sigma}^2_{\varepsilon,i,t}(Y)\right]_{t\in 1970s}. \tag{8}$$

Dividing this by the number of years between the midpoints of the 1970s (1971–1980) and the early 2000s (2001–2006)—in this case, 28 years—yields an annualized long difference in industry i's firm-specific stock return or fundamentals' growths volatilities, denoted $g(\sigma_{\varepsilon,i}{}^2(Y))$, from the 1970s to the 2000s. Annualized long differences in the relative firm-specific volatilities in industry i are similarly defined and denoted as $g(\psi_i(Y))$.

The first number in panel A of table 1 is 1.873, indicating that firm-specific stock return volatility rose, on average, by 1.87% annually from the 1970s to 2000s. From the 1970s to 1990s, it rose by 4.08% annually. This trend reverted sharply in the first decade of the twenty-first century. From the 1990s to 2000s, it decreased by 2.91% annually. Panel B of table 1 shows that relative firm-specific stock return volatility exhibits similar patterns.

Firm-specific volatilities of fundamentals growth rates also increased sharply in the late twentieth century. However, they did not show sharp decreases in the early twenty-first century evident in stock returns, perhaps exhibiting artificial persistence due to overlapping estimation windows.

B. *Relationship between Volatility Measures: The Role of TFP Volatility*

The large late-twentieth-century increase in firm-specific TFP growth volatility relative to firm-specific input growth volatilities (table 1) and the close relationship between R^2 measures of TFP growth rate volatility and output growth volatility (figure 2) suggest a structural change associated with productivity—such as technological innovation—underlying the patterns we identify in firm-specific output growth volatility.

A quick (and econometrically dirty) way of doing this is to regress components of either output growth rate or stock return volatility on components of TFP, labor, and capital growth rate volatilities. If common factors are driving each volatility, this may be subject to endogeneity issues but is nonetheless a useful first pass.

Table 2 displays cross-sectional weighted least squares (WLS) regressions, weighted by 1970s average industry assets, explaining annualized long differences in industries' firm-specific output growth rate or stock return volatilities with firm-specific fundamentals growth rate volatilities. Long differences in an industry's firm-specific TFP volati-

TABLE 2.—FIRM-SPECIFIC TFP VOLATILITY EXPLAINING FIRM-SPECIFIC OUTPUT GROWTH AND STOCK RETURN VOLATILITIES

	Firm-Specific Output Growth Rate Volatility Long Difference from		Relative Firm-Specific Output Growth Rate Volatility Long Difference from	
	1970s to 1990s	1990s to 2000s	1970s to 1990s	1990s to 2000s
A. Dependent Variable: Long Differenced Firm-Specific Output Growth Volatility				
Long difference in firm-specific TFP growth rate volatility	0.560*	0.446*	0.751*	0.293
	(0.000)	(0.000)	(0.000)	(0.112)
Long difference in firm-specific labor growth rate volatility	0.366*	0.586*	0.229	−0.063
	(0.001)	(0.000)	(0.351)	(0.748)
Long difference in firm-specific capital growth rate volatility	0.067	−0.072	0.314*	0.322
	(0.190)	(0.502)	(0.024)	(0.106)
Intercept	0.792*	−0.002	−0.486	−0.627
	(0.038)	(0.993)	(0.435)	(0.449)
Adjusted R^2	0.891	0.764	0.740	0.290
Sample size	42	42	42	42
B. Dependent Variable: Long Differenced Firm-Specific Stock Return Volatility				
Long difference in firm-specific TFP growth rate volatility	0.415*	0.127	0.216*	−0.007
	(0.000)	(0.308)	(0.010)	(0.912)
Long difference in firm-specific labor growth rate volatility	0.375*	−0.156	−0.089	−0.070
	(0.000)	(0.498)	(0.451)	(0.357)
Long difference in firm-specific capital growth rate volatility	−0.064	0.090	0.122	0.129*
	(0.355)	(0.687)	(0.219)	(0.054)
Intercept	−0.120	−3.293*	2.492*	−3.074*
	(0.854)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.755	0.019	0.527	0.051
Sample size	42	42	42	42

Long differences in firm-specific output or stock return volatility are regressed on long differences in firm-specific TFP and input volatilities. Variables and decade windows are defined as in table 1. Observations are weighted by industry total assets averaged across the 1970s. The industry cross-section sample excludes the finance sector (SIC 6000–6999). Numbers in parentheses are probability levels, based on heteroskedasticity-adjusted t-statistics, at which the null hypothesis of a 0 coefficient is rejected. Asterisks denote significance at 10% or better.

lity best explain long differences in its firm-specific output volatility—from both the 1970s to the 1990s when firm-specific volatilities rose and the 1990s to the 2000s when the rise abated or reversed. Long differences in firm-specific TFP volatility also best explain long differences in its firm-specific stock return volatility from the 1970s to the 1990s, but none of the fundamentals' volatility measures work well after 2000—perhaps because the right-hand-side variables, which are all constructed using ten-year overlapping windows, are more persistent than the stock return volatility measures, which are estimated from monthly data over nonoverlapping annual windows. WLS and OLS (not shown) regressions yield similar results, indicating that neither very large nor very small industries drive the result.

The patterns in table 2, emphasizing the role of TFP volatility in explaining both output and stock return volatilities, are strong enough to be readily visible in the data. Figure 3 sorts industries by their annualized growths in the firm-specific output growth volatility and then displays the other firm-specific volatility growth rates of each industry for comparison. The figure clearly shows industries with elevated firm-specific output growth volatility exhibiting elevated firm-specific TFP growth volatility, but not always elevated firm-specific input growth rate volatilities.

Four of the ten industries posting the highest increases in firm-specific output growth volatility are in manufacturing, consistent with a technology shock to these sectors. Underscoring this, two of the top ten—chemicals (including pharmaceuticals) and industrial machinery—are commonly considered high-tech sectors. Two others, electric and gas services and telephones, were recently deregulated, consistent with abrupt changes in competition also having a role to play. However, figure 3 also shows the great majority of sectors exhibiting escalating firm-specific volatility, clearly indicating that the phenomenon is not restricted to a few industries.

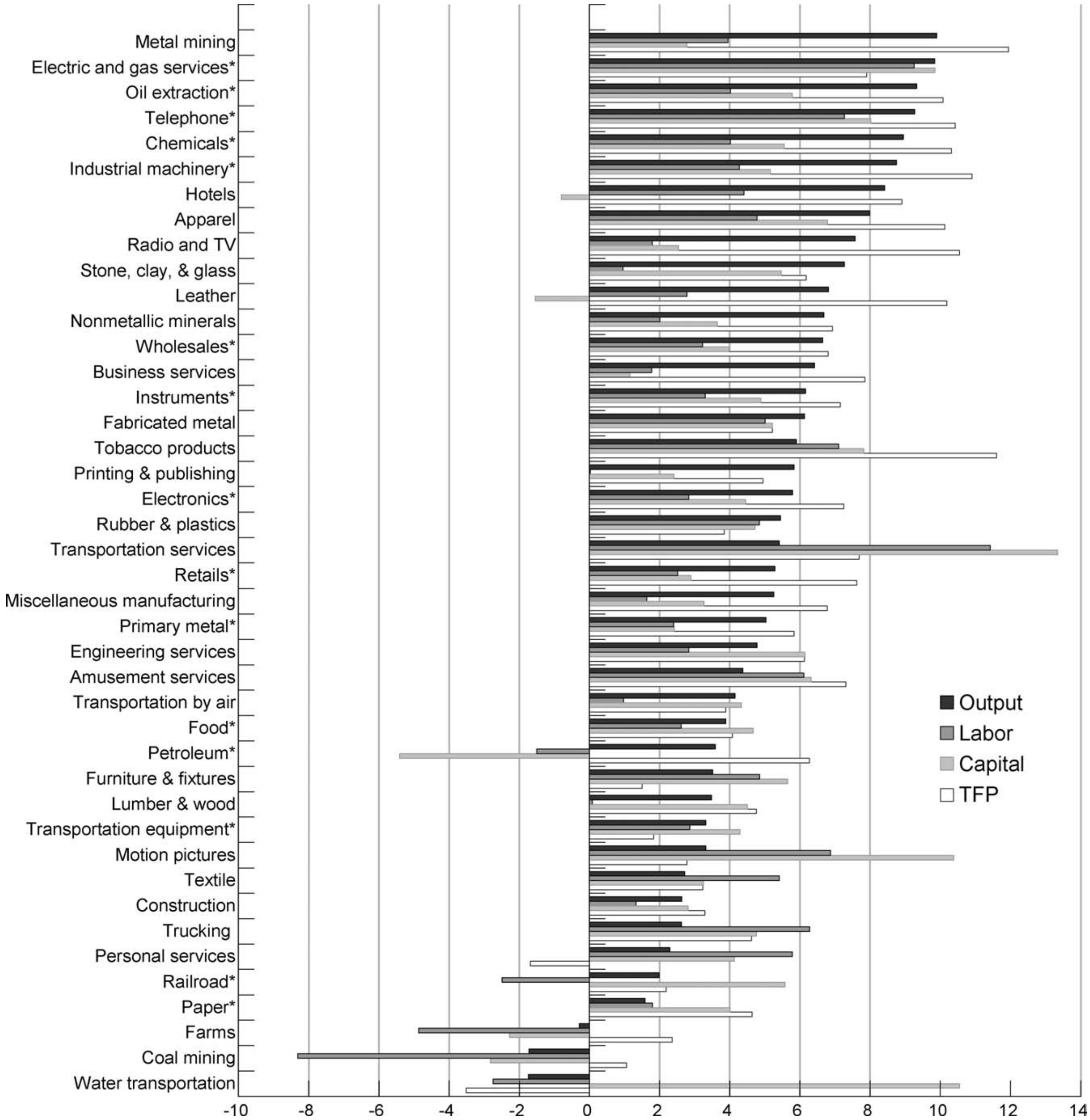
Table 2 and figure 3 thus suggest that the importance of TFP over inputs in explaining firm-level output growth volatility. They also suggest that elevated firm-level and firm-specific stock return volatility cannot be solely attributed to episodes of noise trading (Brandt et al., 2010). Rather, fundamentals change too, and in ways suggesting factors related to episodes of innovation are at work, validating the general thrust of the arguments in Comin and Mulani (2007), Chun et al. (2008), and others. Because stock return volatilities and TFP volatilities are the most forward looking and innovation related, respectively, of our volatility measures, the following sections focus on them.

IV. Underlying Economics

A. Possible Economic Underpinnings

In this section, we examine regularities that might illuminate the economic underpinnings of the findings in the previous section. We do this by constructing proxies for industry characteristics that might correlate with the firm-specific volatilities of stock returns and TFP growth rates. We first consider factors directly related to new technologies (IT and R&D) and then other factors, such as firm demography

FIGURE 3.—GROWTH IN INDUSTRY FIRM-SPECIFIC VOLATILITY



Twenty-year long-differences in firm-specific volatility measures are logarithms of means across the 1990s (1991–2000) less logarithms of means across the 1970s (1971–1980). Reported figures are long differences divided by twenty years or annualized growth rates in firm-specific volatility, in percentage per year. The sample of 42 industries excludes finance industries (SIC 6000–6999) and industries with fewer than five firms. Asterisks denote the 15 largest industries based on output averaged across the 1970s. Data are sorted by growth rate in firm-specific output growth volatility.

and intensified competition, that might also affect firm-specific growth rate volatility as explained below.

Information technology. Bresnahan and Trajtenberg (1995), Helpman and Trajtenberg (1998), Jovanovic and Rousseau (2005), Chun et al. (2008), Pastor and Veronesi (2009), and others argue that IT in the late twentieth century was a GPT—a phenomenon like steam engines in the nineteenth century or electrification in the early twentieth century, which induces a broad wave of innovation across the entire economy. A GPT thus differs from a typical innovation, which affects only one firm or, at most, one industry.

A GPT can render firms more heterogeneous because some realize the productivity gains on offer more fully than others. The latter may lack essential skilled labor Bresnahan et al. (2002), organizational capital, or both (Brynjolfsson, Hitt, & Yang, 2002). Long-established firms may confront higher costs of switching technologies than new firms (Hobijn & Jovanovic, 2001). Schumpeter (1912) and Hayek (1941) argue that rare entrepreneurial skills are unevenly distributed across firms and that periods of rapid innovation put a high premium on skill. For these and other reasons, a new GPT might induce highly firm-specific productivity changes as creative destruction separates winner and loser firms.

We follow Chun et al. (2008) in using the FRTW database, from the BEA, which provides annual two-digit industry-level investment in 61 asset classes from 1971 to 2006. We convert capital investment flows into capital stocks using a perpetual inventory model. Thus, industry i's stock of asset class k at time t is

$$K_{i,k,t} = (1 - \delta_k)K_{i,k,t-1} + I_{i,k,t}, \tag{9}$$

with δ_k a depreciation rate and $I_{i,k,t}$ the industry's spending on type k asset in year t. We use asset class depreciation rates from the FRTW (Fraumeni, 1997) in which $\delta_k = 0.31$ for IT.

IT investment is defined as spending on 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 of software (prepackaged, custom, and own-account software). We aggregate asset classes using Törnqvist indexes and estimate industry i's IT intensity in year t as its stock of IT capital relative to other capital:

$$IT_{i,t} \equiv \frac{\sum_{k \in IT} K_{i,k,t}}{\sum_{k \notin IT} K_{i,k,t}}. \tag{10}$$

Chun et al. (2008) show IT capital intensity distributed broadly across industries, as expected of a GPT, and rising through the decades we study. The cross-industry coefficient of variation in the logarithm of IT intensity falls continuously after the early 1990s, indicating an economy-wide penetration by the turn of the century.

Research and development. Research and development (R&D) is another obvious gauge of innovation. Firms spend on R&D to create new products or technologies to boost their productivity and undermine their competitors, thereby elevating firm-specific TFP growth volatility. For example, R&D-intensive firms can engage in fierce patent races, with the winner owning a new productivity-enhancing technology and the loser reaping little from its R&D spending. Comin and Mulani (2007) link firm-level volatility to idiosyncratic innovations associated with firm-level R&D.

IT and R&D are quite likely complements, so sharply distinguishing them may be difficult. This is especially so because a GPT affects all sorts of production processes and is itself "the invention of a method of inventing" (Griliches, 1957). Thus, a GPT such as IT might well enable R&D.[7]

[7] One distinguishing characteristic of IT is its broad adoption across all industries, in contrast to R&D concentration in a few key industries. Although both are obviously useful proxies for innovation, this suggests that IT might track innovation across a wider swath of industries. Our focus on IT reflects studies positing IT as a GPT and in no way challenges the validity of R&D as a proxy for innovation. In other settings, R&D might be the preferable variable.

We construct a measure of industry-level R&D capital from annual R&D spending (Compustat item 46) as in equation (9), but assuming a 20% depreciation rate and using the GDP deflator, as in Chan, Lakonishok, and Sougiannis (2001). Each industry's R&D intensity is its capitalized R&D over its property, plant, and equipment (PP&E, item 8), a ratio analogous to equation (10).

Corporate demography. Our Compustat database is restricted to listed firms, and U.S. exchanges list ever newer and smaller firms over the decades (Pastor & Veronesi, 2003; Fama & French, 2004). Since young and small firms are plausibly riskier than old established firms, escalating firm-specific volatility in various performance measures might reflect this changing demography of listed firms. We measure a firm's age as years since its first appearance in CRSP, which corresponds to its first listing on the NYSE, AMEX, or NASDAQ. This misses initial public offerings on regional or foreign exchanges and misstates the ages of long-standing private firms that listed late in their lives. Alternative firm age measures are considered in section VB. We define a firm's size as its total sales. Our industry-level regression variables are average firm age, the log of the average age of the industry's firms, and average firm size, as the log of the average sales of its firms.

These variables can be interpreted as tracking financial development; increasingly sophisticated stock exchanges list ever smaller and newer firms (Pastor & Veronesi, 2003; Fama & French, 2004). However, an equally plausible interpretation is that this, like R&D or IT intensity, tracks innovation because innovators often list new firms, finding old, established firms loath to support radical innovations (Schumpeter, 1912). Hobijn and Jovanovic (2001) develop this argument in the context of IT, arguing that older firms' resources are geared to running older technology, making new IT-based innovations less attractive to them. Consequently, an increased prominence of small, young firms in U.S. equity markets, especially in the late twentieth century, might also reflect a wave of innovation.

Intensified competition. Escalating firm-specific stock return and TFP growth volatilities might reflect intensified competition (Philippon, 2003; Gaspar & Massa, 2006; Irvine & Pontiff, 2009). Irvine and Pontiff (2009) model intensified price competition as magnifying small mistakes into disasters and small economic profits into lasting leads. Like corporate demography, innovation is unlikely to be entirely independent of innovation. For example, Brown and Goolsbee (2002) link Internet growth to falling term life premiums, consistent with lower search costs on the Web stimulating price competition. To proxy for product market competition in each industry, we therefore construct annual Herfindahl-Hirschman indexes based on the annual sales of all firms in that industry, as reported in Compustat.

Irvine and Pontiff (2009) further suggest that deregulation in the 1980s and early 1990s might have magnified firm-specific volatilities by letting firms previously tightly constrained by regulators adopt new and unique strategies. Since some of these were ultimately more successful than others, enhanced firm-specific volatilities in stock returns and TFP growth rates could ensue. However, if new strategies are considered yet another form of innovation, this thesis too folds into our working hypothesis. Nonetheless, we introduce the indicator variable, δ_{dereg}, set to 1 for extensively deregulated industries and to 0 for others. Deregulated industries are railroad, trucking, transportation by air, telephones, electric and gas services, and motion pictures—all as in Winston (1998).[8]

B. Regressions

Using industry panel data from 1971 to 2006, we regress firm-specific stock return volatility on IT intensity and the other variables discussed above. Our dependent variable is the log of firm-specific stock return volatility for industry i's year t, $\ln(\sigma_{\varepsilon,i,t}{}^2)$, either alone or relative to the log of the industry's systematic volatility. The latter, called the log of relative firm-specific volatility and denoted $\ln(\psi_{i,t})$, is closely related to the R^2 measure in figure 2 because

$$ln(\psi_{i,t}) \equiv ln\left(\frac{1-R^2_{i,t}}{R^2_{i,t}}\right) = ln(\sigma^2_{\varepsilon,i,t}) - ln(\sigma^2_{s,i,t}). \tag{11}$$

We estimate WLS panel regressions, weighting observations by prior year total industry assets and including industry and time fixed effects:

$$\begin{aligned} ln(\sigma^2_{\varepsilon,i,t}) = b_0 + b_1\, ln(IT_{i,t-1}) + b_2\, ln(\sigma^2_{s,i,t-1}) \\ + BX_{i,t-1} + \mu_i + \eta_t + u_{i,t}, \end{aligned} \tag{12}$$

$$ln(\psi_{i,t}) \;= b_0 + b_1\, ln(IT_{i,t-1}) + BX_{i,t-1} + \mu_i + \eta_t + u_{i,t}, \tag{13}$$

where the dependent variables in equations (12) and (13) are the log of firm-specific stock return volatility and the log of relative firm-specific volatility, respectively. IT intensity, denoted IT, is the ratio of IT to non-IT capital stocks, and X is a vector of other variables. Both IT and X are lagged to mitigate endogeneity issues, which are dealt with more directly by instrumental variables regressions in section VA. Standard errors are clustered by industry, adjusting for heteroskedasticity and autocorrelation, as in Petersen (2009).[9] Using relative firm-specific volatility as the dependent variable in equation (13) de facto constrains the coefficient of systematic volatility in equation (12) to equal 1. In this sense, equation (12) is a more flexible specification. Panel A of table 3 displays summary statistics for our dependent and independent variables in panel regressions.

The regressions (12) and (13) use annual panel data because stock return volatility is measured in nonoverlapping annual windows. In contrast, TFP volatility is measured in ten-year rolling windows. To mitigate problems due to overlapping estimation windows, their analogs explaining firm-specific TFP volatility are

$$\begin{aligned} \Delta\, ln[\sigma^2_{\varepsilon,i}(TFP)] = c_0 + c_1 \Delta\, ln(IT_i) \\ + c_2 \Delta\, ln[\sigma^2_{s,i}(TFP)] + C\Delta X_i + e_i, \end{aligned} \tag{14}$$

$$\Delta\, ln[\psi_i(TFP)] = c_0 + c_1 \Delta\, ln(IT_i) + C\Delta X_i + e_i, \tag{15}$$

where the dependent and independent variables are long differences,[10] defined as averages from 1991 through 2006 less averages through the 1970s. Observations are weighted by industry total assets averaged across the 1970s to mitigate endogeneity issues, addressed below more fully in instrumental variable regressions. Long differencing obviates industry fixed effects and, by rendering equations (14) and (15) simple cross-sectional regressions, obviates the need for industry clustering. Standard errors are, however, adjusted for heteroskedasticity. Panel B of table 3 displays summary statistics for our dependent and independent variables in these regressions.

C. Regression Results

Table 4 reports estimates of regressions in equations (12) and (13), respectively, along with p-values based on industry clustering. The table clearly associates elevated IT intensity with elevated firm-specific stock return volatility, regardless of whether it stands alone or alongside the other variables.

Our other technology variable, R&D intensity, is significant in equation (12) but with much smaller coefficients than those of IT intensity. However, it is not significant in equation (13). We interpret this as supporting the basic conclusions of Comin and Philippon (2005), who link R&D intensity to firm-level volatility, but suggesting that IT intensity better gauges broad-based technological changes, at least during this period, consistent with IT being a GPT.[11]

Prior research, mainly using data ending in 2000, indicates that both average firm size and average firm age

[8] Acemoglu (2005) points out that deregulation, pertaining to a handful of industries, is unlikely to explain economy-wide elevations in firm-specific volatility.

[9] Petersen (2009) uses Monte Carlo analyses to show that White, Newey-West, Fama-Macbeth, and other widely used panel estimation techniques overstate t-ratios if the data include autocorrelated or persistent variables, even if fixed or random effects are included. Clustered standard errors, in contrast, allow unbiased significance tests.

[10] We also use annual overlapping annual TFP volatility measures in panel regressions, including both industry and time fixed effects with clustered standard errors. Results from these regressions are qualitatively similar to those obtained from long-difference regressions.

[11] As in studies on economic growth, R&D intensity can be defined as R&D spending over either GDP or sales, that is, as the ratio of flow variables (Comin & Philippon, 2005). Using this definition of R&D intensity yields qualitatively similar results to those in the tables.

TABLE 3.—SUMMARY STATISTICS FOR VARIABLES USED IN REGRESSIONS

		Mean	Median	Standard Deviation	Minimum	Maximum
A. Variables in Firm-Specific Stock Return Volatility Panel Regressions, 1971–2006						
Stock return volatility measures						
Firm-specific volatility	$\ln(\sigma_\varepsilon^2)$	−4.413	−4.421	0.736	−6.500	−2.319
Relative firm-specific volatility	$\ln(\psi)$	0.801	0.836	0.474	−0.848	2.658
Systematic volatility	$\ln(\sigma_s^2)$	−5.195	−5.224	0.706	−7.390	−2.204
Technological progress						
Information technology intensity	$ln(IT)$	−5.004	−4.798	2.111	−10.428	−0.031
R&D intensity	$\ln(R\&D)$	−4.241	−3.539	3.242	−17.211	−0.241
Corporate demography						
Industry mean firm age	$\ln(Age)$	2.740	2.726	0.420	0.673	4.007
Industry mean firm size	$\ln(Size)$	7.390	7.227	1.154	3.597	10.425
Competition						
Industry Herfindahl index	H	0.066	0.049	0.068	0.007	0.620
B. Variables in Firm-Specific TFP Growth Rate Volatility Long-Difference Regressions, based on Long Differences from 1970s (1971–1980) to 1991–2006.						
TFP growth volatility measures						
Firm-specific volatility	$\Delta\ln(\sigma_\varepsilon^2)$	1.621	1.586	0.552	−0.200	2.500
Relative firm-specific volatility	$\Delta\ln(\psi)$	0.435	0.416	0.581	−1.214	1.811
Systematic volatility	$\Delta\ln(\sigma_s^2)$	1.120	1.007	0.612	−0.551	3.994
Technological progress						
Information technology intensity	$\Delta\ln(IT)$	3.675	3.851	0.792	2.213	4.721
R&D intensity	$\Delta\ln(R\&D)$	0.058	0.076	0.638	−1.546	2.506
Corporate demography						
Industry mean firm age	$\Delta\ln(Age)$	0.205	0.255	0.242	−0.585	0.805
Industry mean firm size	$\Delta\ln(Size)$	0.738	0.754	0.669	−1.234	2.180
Competition						
Industry Herfindahl index	ΔH	−0.030	−0.004	0.072	−0.221	0.146
Deregulated industry dummy	δ_{dereg}	0.331	0.000	0.478	0.000	1.000

Volatility measures and decade windows are defined as in table 1. Information technology intensity (ln(*IT*)): The logarithm of IT capital (computers and software) over other capital. Research and development intensity (ln(*R&D*)): The logarithm of capitalized past R&D spending over property, plant, and equipment. Mean firm age (ln(*Age*)): The log of industry-average years listed in CRSP. Mean firm size (ln(*Size*)): The log of industry-average sales. Industry Herfindahl index (*H*): Sales based. The deregulated industry dummy, δ_{dereg}, is 1 for deregulated industries and 0 otherwise. Long differences are indicated by Δ, and in panel B, these are increases from the 1970s to the 1990s and 2000s (1991–2006, inclusive). Observations are weighted by prior-year industry total assets and by industry total assets averaged across the 1970s in panels A and B, respectively. The sample in panel A is a 1,452 U.S. industry-year panel excluding the finance sector (SIC 6000–6999); that in panel B is a cross-section of 34 U.S. industries.

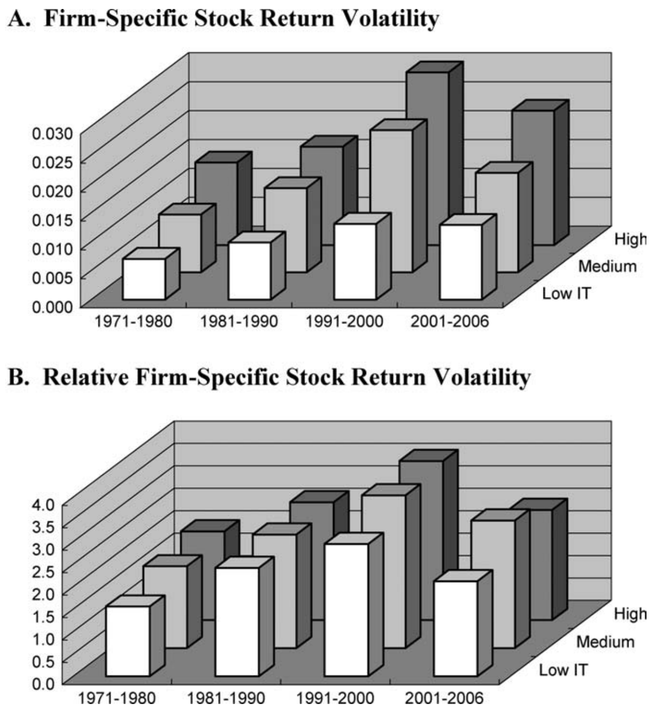
TABLE 4.—PANEL REGRESSIONS EXPLAINING FIRM-SPECIFIC STOCK RETURN VOLATILITY

	Logarithm of Firm-Specific Stock Return Volatility				Logarithm of Relative Firm-Specific Stock Return Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technological progress								
$\ln(IT)$	0.199*	0.176*	0.200*	0.177*	0.112*	0.107*	0.113*	0.108*
	(0.000)	(0.006)	(0.000)	(0.007)	(0.011)	(0.015)	(0.011)	(0.017)
$\ln(IT) \times \delta_{2000}$			0.012	0.007			−0.018	−0.013
			(0.651)	(0.820)			(0.527)	(0.657)
$\ln(R\&D)$		0.035*		0.035*		0.002		0.002
		(0.032)		(0.031)		(0.832)		(0.782)
Corporate demography								
$\ln(Age)$		−0.382*		−0.380*		0.047		0.049
		(0.017)		(0.017)		(0.663)		(0.648)
$\ln(Size)$		−0.050		−0.049		−0.045		−0.044
		(0.282)		(0.304)		(0.266)		(0.284)
Competition								
H		−0.907		−0.915		0.241		0.225
		(0.221)		(0.221)		(0.474)		(0.496)
Systematic volatility								
$\ln(\sigma_s^2)$	0.239*	0.178*	0.241*	0.179*				
	(0.000)	(0.000)	(0.000)	(0.000)				
Adjusted R^2	0.817	0.828	0.817	0.828	0.581	0.582	0.581	0.582
Sample size	1,452	1,452	1,452	1,452	1,452	1,452	1,452	1,452

Volatility measures are defined as in table 1, and other explanatory variables are defined as in table 3. The indicator variable, δ_{2000}, is 1 for 2001 to 2006 and 0 otherwise. IT intensity and controls are lagged by one year. All regressions include industry and time fixed effects. Observations are weighted by lagged total assets. The sample period is 1971 to 2006. The sample is a U.S. industry-year panel excluding the finance sector (SIC 6000–6999), industries with fewer than five firms, and industries for which explanatory variables are unavailable. Numbers in parentheses are probability levels for rejecting the null hypothesis of a zero coefficient. Standard errors are clustered by industry, adjusting for heteroskedasticity and autocorrelation. Asterisks denote significance at 10% or better.

correlate with firm-specific volatility. We confirm negative and significant coefficients for these variables in regressions of firm-specific volatility in that sample period. However, extending the data until 2006 leaves both variables insignificant when included alone, though age recovers significantly if included alongside size. The sporadic significance

FIGURE 4.—CROSS-INDUSTRY DISTRIBUTION OF FIRM-SPECIFIC STOCK RETURN VOLATILITY AND IT INTENSITY



of these variables underscores stable and consistently positively significant IT coefficients across specifications.

Because our regressions include time fixed effects, we control for general-level changes in the variables. Still, the cross-sectional relationship between IT intensity and firm-specific volatility might differ in periods of increasing versus decreasing volatility. To examine this, we include a slope shifter that is equal to IT intensity in 2001 through 2006 and 0 in other years. Table 4 shows no significant difference in the coefficient of IT intensity in the two subperiods.[12] A statistically indistinguishable relationship thus links IT intensity and firm-specific volatility in periods of both rising and falling firm-specific volatility. This stability is also evident in figure 4, which graphs industry-average firm-specific volatilities across time periods and by industry IT intensity tertiles. Thus, although volatilities increase and then decrease over the decades, the cross-sectional monotonic relationship of firm heterogeneity to IT intensity does not change. This rising and ebbing of firm volatility that overlays a stable, positive relationship between volatility and IT intensity suggests a possible propagation mechanism for GPTs, or at least for IT. In an initial stage of propagation, the gap between successful and unsuccessful adopters widens with time. For example, successful early adopters might be difficult to mimic initially, and their benefits of innovation might accumulate as other firms drop behind. In a later stage, when other firms also adopt the innovation successfully and the new technology propagates fully, heterogeneity falls. Behind these time-series variations of rising and falling firm heterogeneity lies a stable cross-sectional relationship between the two variables, suggesting a normal level of heterogeneity reflecting differing levels of IT intensity across industries.

Table 5 reports our long-difference regressions of firm-specific TFP growth volatility, equations (14) and (15). As in table 4, table 5 confirms the robustness and stability of the relationship between IT intensity and firm-specific volatility. Table 5 also reports results using long differences constructed across alternative time windows—from the 1970s to the 1990s and from the 1970s to the period 2001 to 2006. Using these alternative long differences sample periods generates the same pattern of signs and significance: IT intensity is significantly related to firm-specific volatility, while our other variables are either insignificant or only sporadically significant, and their inclusion or exclusion leaves the coefficient of IT intensity essentially unchanged. These results indicate that long-term changes in IT intensity correlate with long-term changes in firm-specific volatility similarly regardless of whether the change is from the 1970s to the 1990s, a period of rising volatility, or from the 1970s to the post-2000 period, when firm-specific volatility ebbs again.

In summary, our regression results are consistent with our hypothesis that elevated IT intensity signals a wave of creative destruction elevating firm-specific stock return and TFP growth rate volatilities across the economy, industry by industry. This reinforces previous arguments that IT is a general-purpose technology—an innovation sweeping across most or all traditional industries as well as the IT sector itself. This finding need not preclude R&D investment, corporate demography, or product market competition from affecting firm-specific volatility too. Indeed, the likelihood that these also capture aspects of intensified innovation suggests they should matter, at least in some contexts. However, tables 4 and 5 suggest that intensified IT application is likely the predominant factor elevating firm-specific volatility at the close of the twentieth century.

V. Robustness

A wide range of robustness tests generates results qualitatively similar to those shown in tables 4 and 5, by which we mean that elevated IT intensity correlates significantly with elevated firm-specific volatility across all specifications discussed and that other explanatory variables are intermittently significant, insignificant, or attract inconsistent or perverse signs.

A. *Endogeneity*

Clarifying the economics beneath the overarching importance of IT intensity in explaining firm-specific volatility requires revisiting the issue of endogeneity. Reverse causal-

[12] In a similar vein, we also include two IT variables that are multiplied by the 1971–2000 and 2001–2006 period dummy variables. Both coefficients are statistically significant and are very close to each other.

TABLE 5.—LONG DIFFERENCE REGRESSIONS EXPLAINING FIRM-SPECIFIC TFP GROWTH VOLATILITY

	Long Difference in Firm-Specific Volatility from the 1970s to:				Long Difference in Relative Firm-Specific Volatility from the 1970s to:			
	1991–2006	1991–2006	1990s	2000s	1991–2006	1991–2006	1990s	2000s
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technological progress								
$\Delta\ln(IT)$	0.426*	0.254*	0.198*	0.374*	0.562*	0.404*	0.326*	0.608*
	(0.000)	(0.009)	(0.045)	(0.005)	(0.000)	(0.000)	(0.003)	(0.000)
$\Delta\ln(R\&D)$		−0.0481	−0.038	−0.037		−0.118	−0.088	−0.108
		(0.620)	(0.666)	(0.719)		(0.384)	(0.462)	(0.406)
Corporate demography								
$\Delta\ln(Age)$		−0.408	−0.206	−0.433		0.187	0.430	0.003
		(0.340)	(0.638)	(0.317)		(0.662)	(0.323)	(0.994)
$\Delta\ln(Size)$		−0.025	−0.028	−0.033		−0.058	−0.045	−0.072
		(0.847)	(0.835)	(0.793)		(0.524)	(0.652)	(0.476)
Competition								
ΔH		0.060	0.555	−0.447		1.789	1.899	1.466
		(0.964)	(0.645)	(0.779)		(0.225)	(0.179)	(0.411)
δ_{dereg}		0.374*	0.434*	0.319		0.460*	0.573*	0.180
		(0.018)	(0.007)	(0.159)		(0.004)	(0.001)	(0.372)
Systematic volatility and intercept								
$\Delta\ln(\sigma_s^2)$	0.687*	0.577*	0.647*	0.539*				
	(0.000)	(0.000)	(0.000)	(0.001)				
Intercept	−0.713*	0.234	0.131	−0.407	−1.629*	−1.138*	−0.807*	−2.002*
	(0.015)	(0.954)	(0.765)	(0.472)	(0.000)	(0.006)	(0.040)	(0.001)
Adjusted R^2	0.669	0.694	0.646	0.698	0.572	0.682	0.670	0.599
Sample size	34	34	34	34	34	34	34	34

Volatility measures and decades are defined as in table 1, and other explanatory variables are as in table 3. The dependent variable in columns 1 through 4 is the long difference in firm-specific TFP growth volatility, that is, the logarithm of mean firm-specific TFP growth volatility in the specified later period less the logarithm of its mean in the 1970s (1971–1980). The dependent variable in columns 5 through 8 is the long difference in relative firm-specific TFP growth volatility, that is, in the logarithm of firm-specific TFP growth volatility as a fraction of systematic TFP growth volatility. All explanatory variables beginning with Δ also denote long differences between the same periods used for the dependent variables. The sample is U.S. industries, excluding the finance sector (SIC 6000–6999), industries with fewer than five firms, and industries for which explanatory variables are unavailable. Observations are weighted by industry total assets averaged across the 1970s. Numbers in parentheses are probability levels, based on standard errors adjusted for heteroskedasticity, at which the null hypothesis of a 0 coefficient is rejected. Asterisks denote significance at 10% or better.

ity is possible if, for example, firms respond to intensified firm-specific shocks with IT investment to better manage business risk. For example, Comin (2000) models how uncertainty raises the demand for flexible capital. Using U.S. manufacturing industry data from the 1960s to 1980s, he shows that industries experiencing high uncertainty, measured by ten-year lagged stock return standard deviations, buy more computers.

To assuage this concern, we construct two instrumental variables to be exogenous to buyers of IT assets: the tax rates on IT assets and the marginal cost of IT production. The tax rates on IT assets may well lie beyond the control of individual firms. However, political lobbying affects tax rates. IT producers are few, and IT consumers, given that IT is a GPT, span the entire economy. Olson (1971) shows that smaller interest groups are effective lobbyers, while large, diffuse groups, hindered by collective action problems, are not. This implies that tax rates on IT assets are less likely to be exogenous variables for IT-producing industries. Moreover, the marginal cost of IT production is clearly endogenous to IT-producing firms and industries. We therefore drop two IT-producing industries from our IV regressions.[13]

We take an industry's net tax rate on IT, $Tax_{i,t}$, to be the weighted average of the tax rates, net of subsidies, applicable to the various classes of IT assets used in that industry. Weights are the relative intensities of each IT asset class in that sector, that is,

$$Tax_{i,t} \equiv \sum\nolimits_{k \in IT} W_{i,k,t} Tax_{k,t}, \tag{16}$$

where $W_{i,k,t} = K_{i,k,t} / \sum_{k \in IT} K_{i,k,t}$ and $Tax_{k,t} \equiv (1 - \zeta_{k,t} - u_t z_{k,t})/(1 - u_t)$ is an asset-specific net tax rate for IT asset class 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 are all from the BLS.

The variable defined by equation (16) should correlate with IT intensity since higher taxes on the IT assets an industry needs should lower its demand for those assets, ceteris paribus.

Although the IT asset class tax rates $\{Tax_{k,t}\}$ are exogenous to non-IT-producing industries, the IT asset weights in equation (16) might be endogenous if, for example, industries with higher IT intensity prefer a specific type of IT asset, inducing an artificial positive relationship between its weight and IT intensity. If so, $Tax_{i,t}$, the inner product of a vector of IT asset tax rates and IT asset usage weights for each industry, might not be entirely exogenous, and the relationship between the instrument, equation (16), and IT intensity might be driven by the weights themselves in that equation, rather than by the weighted average of IT asset tax rates.[14]

[13] Retaining these two industries generates qualitatively similar results.

[14] We are grateful for an anonymous referee for suggesting a possible endogeneity issue regarding weights.

To check this, we first test for correlations between weights and IT intensity. A panel regression, clustering by industry, of $IT_{i,t}$ on the eleven IT asset class weights, $W_{i,k,t}$, yields seven insignificant coefficients, three significant negative coefficients, and one significant positive coefficient. The weights whose coefficients are insignificant cannot be driving our results; however, the others are a potential problem, which implies that possible built-in correlation between weights and IT intensity might drive our results. To see if the weights are driving our results, we create a normal random variable with the same mean and variance as the IT asset class tax rates $\{Tax_{k,t}\}$ and then conduct Monte Carlo tests, replicating equation (16) 100 times with these randomly drawn tax rates. We find the resulting 100 industry IT tax rates are insignificantly correlated with IT intensity. Another Monte Carlo exercise, replicating equation (16) 100 times by drawing randomly, with or without replacement, from the sample of actual IT class rates $\{Tax_{k,t}\}$ also yields insignificant correlations.

If the weights were inducing an artificial correlation between equation (16) and IT intensity, these insignificant results would not be observed. We thus conclude that any correlation of the instrument $Tax_{i,t}$ defined in equation (16) with IT intensity reflects the genuine economic costs that an industry confronts in purchasing IT assets and proceed assuming the instrument is exogenous. We revisit the validity of this instrument below with a formal weak instrument and overidentifying restriction tests in connection with our two-stage least squares (2SLS) regressions.

Our second instrument is the marginal cost of IT production relevant to each industry each year, defined as in equation (16) but replacing asset-specific net tax rates with a proxy for asset-specific marginal cost of IT asset class k in year t, denoted $MCQ_{k,t}$:

$$MCQ_{i,t} = \sum\nolimits_{k \in IT} W_{i,k,t} MCQ_{k,t}, \tag{17}$$

where $W_{i,k,t} = K_{i,k,t} / \sum_{k \in IT} K_{i,k,t}$. Because observed marginal costs are affected by both demand and supply, we need the $MCQ_{k,t}$ to proxy for supply-side determinants only. To this end, we estimate $MCQ_{k,t}$ as a marginal cost of IT quality for each IT asset class k in each period t. To do this, we assume the quality of an IT asset class to be inversely proportional to its hedonic price, adjusted for changes in its list price. Following Chun and Nadiri (2008), we construct a marginal cost of quality for four IT asset classes.[15] Our marginal cost of IT production for a given industry in a given year is defined as a weighted average of these four marginal costs of quality using the weights in equation (16). We repeat the Monte Carlo exercises and again find insignificant correlations between equation (17) and IT intensity.

Tables 6 and 7, using two-stage regressions with the above instrumental variables for IT intensity, generate results qualitatively similar to those in tables 4 and 5. This suggests that endogeneity is not greatly biasing the first set of results and demonstrates that exogenous variation in instrumentalized IT intensity, which mainly reflects changes in supply-side conditions and is independent of the endogenous need for IT capital discussed in Comin (2000), causes higher firm-specific volatility.[16]

Tables 6 and 7 let us reassess our instruments. They pass conventional weak instrument tests, both separately and jointly, with first-stage F-statistics well above 10 (Stock & Yogo, 2005) and generate statistically significant and stable second-stage IT coefficients. Consistently, overidentification tests also generate p-levels consistent with the exogeneity of the instruments. In contrast, all of the various "false" instruments we created, using artificially generated IT asset class tax rates and marginal costs of quality, drawn from all our various Monte Carlo exercises, fail weak instruments tests and generate uniformly insignificant second-stage coefficients on IT intensity. Overall, our two-stage regressions and attendant Monte Carlo robustness checks confirm the significance of shifting IT intensity.

B. *Initial Public Offerings*

The 1980s and 1990s saw a wave of initial public offering (IPO) activity.[17] Davis et al. (2006) show that firms went public younger in the 1980s and 1990s than in previous decades. Consequently, sample composition effects might have a significant role in the rising firm-specific volatility during this period. Although tables 4 and 5 control for industries' average firm age, measured as the number of years the average firm in the industry has been listed on a national exchange, this measure may underestimate true age if firms initially listed on regional exchanges or existed as private firms for long periods before going public.

This effect is potentially important, for Fink et al. (2005) link the positive time trend they observe in firm-specific volatility to firms listing at early ages in later years by running time-series regressions of average firm-specific volatility against variables measuring the market capitalization of relatively young firms and showing the residuals of this regression to exhibit no time trend. We repeat this exercise, running a time-series regression of average firm-specific volatility on IT intensity, and this also yields residuals with no time trend. This, in conjunction with the findings of Fink et al. (2005), suggest that Jovanovic and Rousseau (2001) may be correct in arguing that IT is a new GPT that induces firms to list sooner to tap risk-tolerant equity financing.

[15] Since these estimates from Chun and Nadiri (2008) are available only through 1999, we use the sample period of 1971–2000 when the marginal cost instrument is used.

[16] Of course, this need not preclude causation in the opposite direction. Thus, these results, in conjunction with Comin's (2000) linking of elevated volatility to elevated IT investment for managing risk, suggest bidirectional causality. We thank an anonymous referee for pointing this out.

[17] We are grateful for an anonymous referee for suggesting this analysis.

TABLE 6.—TWO-STAGE PANEL REGRESSIONS EXPLAINING FIRM-SPECIFIC STOCK RETURN VOLATILITY

	Logarithm of Firm-Specific Volatility				Logarithm of Relative Firm-Specific Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technological progress								
ln(*IT*)	0.375*	0.381*	0.358*	0.342*	0.200*	0.192*	0.191*	0.180*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.003)
ln(*R&D*)		0.023		0.024		−0.002		−0.010
		(0.253)		(0.135)		(0.859)		(0.405)
Corporate demography								
ln(*Age*)		−0.331*		−0.192		0.054		0.035
		(0.009)		(0.148)		(0.573)		(0.756)
ln(*Size*)		−0.046		−0.082		−0.034		−0.043
		(0.364)		(0.183)		(0.503)		(0.462)
Competition								
H		−1.115		−1.223		0.202		0.160
		(0.165)		(0.121)		(0.537)		(0.560)
Systematic volatility								
$\ln(\sigma_s^2)$	0.212*	0.147*	0.194*	0.150*				
	(0.000)	(0.002)	(0.001)	(0.002)				
Instruments	*Tax*	*Tax*	*Tax, MCQ*	*Tax, MCQ*	*Tax*	*Tax*	*Tax, MCQ*	*Tax, MCQ*
Weak instruments test	702.94	671.26	416.10	393.31	736.42	702.02	433.62	405.69
Overidentification test	NA	NA	2.235	0.609	NA	NA	1.807	1.582
			(0.135)	(0.435)			(0.179)	(0.208)
Adjusted R^2	0.791	0.801	0.788	0.798	0.563	0.565	0.614	0.615
Sample size	1,380	1,380	1,148	1,148	1,380	1,380	1,148	1,148

Volatility measures are defined as in table 1, and explanatory variables are defined as in table 3. Dependent variables in columns 1 through 4 and 5 through 8, respectively, are logarithms of firm-specific and relative firm-specific stock return volatility. IT intensity is estimated in a first-stage regression with either IT tax rates (*Tax*) or both *Tax* and the marginal cost of IT production (*MCQ*) as instrumental variables. All regressions include industry and time fixed effects. Observations are weighted by lagged total assets. The sample period is 1971 to 2006, but the sample period for columns using *MCQ* as an instrument is 1971 to 2000 due to more limited data availability. The sample is a U.S. industry-year panel excluding the finance sector (SIC 6000–6999), industries with fewer than five firms, industries for which explanatory variables are unavailable, and two IT-producing industries. Numbers in parentheses are probability levels for rejecting the null hypothesis of a 0 coefficient. Standard errors are clustered by industry, adjusting for heteroskedasticity and autocorrelation. Asterisks denote significance at 10% or better. Weak instruments tests are *F*-statistics for the instruments in first-stage regressions. Overidentifying restrictions tests are chi-squared statistics; numbers in parentheses are probability levels for rejecting the null hypothesis that the excluded instruments are valid.

TABLE 7.—TWO-STAGE LONG-DIFFERENCE REGRESSIONS EXPLAINING FIRM-SPECIFIC TFP GROWTH VOLATILITY

	Long Difference in Firm-Specific Volatility from the 1970s to 1991–2006				Long Difference in Relative Firm-Specific Volatility from the 1970s to 1991–2006			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technological progress								
Δln(*IT*)	0.428*	0.206*	0.436*	0.234*	0.634*	0.389*	0.649*	0.411*
	(0.000)	(0.086)	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)
Δln(*R&D*)		−0.087		−0.065		−0.148		−0.114
		(0.222)		(0.328)		(0.206)		(0.304)
Corporate demography								
Δln(*Age*)		−0.347		−0.175		0.328		0.494
		(0.319)		(0.585)		(0.368)		(0.140)
Δln(*Size*)		−0.154		−0.172*		−0.132*		−0.156*
		(0.130)		(0.075)		(0.055)		(0.016)
Competition								
Δ*H*		−1.266		−1.598		0.663		0.272
		(0.231)		(0.115)		(0.600)		(0.819)
δ_{dereg}		0.365*		0.321*		0.406*		0.368*
		(0.056)		(0.051)		(0.006)		(0.006)
Systematic volatility and intercept								
$\Delta\ln(\sigma_s^2)$	0.676*	0.495*	0.687*	0.531*				
	(0.000)	(0.000)	(0.000)	(0.000)				
Intercept	−0.705*	0.325	−0.754*	0.158	−1.880*	−1.069*	−1.942*	−1.175*
	(0.024)	(0.505)	(0.014)	(0.679)	(0.000)	(0.010)	(0.000)	(0.001)
Instruments	*Tax*	*Tax*	*Tax, MCQ*	*Tax, MCQ*	*Tax*	*Tax*	*Tax, MCQ*	*Tax, MCQ*
Weak instruments test	52.16	19.02	25.67	9.81	58.10	23.79	28.85	12.53
Overidentification test	NA	NA	0.045	0.003	NA	NA	2.075	0.016
			(0.832)	(0.958)			(0.150)	(0.899)
Adjusted R^2	0.696	0.751	0.710	0.781	0.617	0.698	0.617	0.732
Sample size	32	32	31	31	32	32	31	31

Volatility measures and decades are defined as in table 1, and other explanatory variables are defined as in table 3. The dependent variable in columns 1 through 4 is the long difference in firm-specific TFP growth volatility: the logarithm of that variable's mean across the 1990s and 2000s (1991–2006) less the logarithm of its mean in the 1970s (1971–1980). The dependent variable in columns 5 through 8 is a similarly defined long difference in relative firm-specific TFP growth volatility. All explanatory variables beginning with Δ also denote long differences across the same periods as used in the dependent variable's construction. IT intensity is estimated in a first-stage regression with either IT tax rates (*Tax*) or both *Tax* and the marginal cost of IT production (*MCQ*) as instrumental variables. The sample is U.S. industries excluding the finance sector (SIC 6000–6999), industries with fewer than five firms, industries for which explanatory variables are unavailable, and two IT-producing industries. Observations are weighted by industry total assets averaged across the 1970s. Numbers in parentheses are probability levels, based on standard errors adjusted for heteroskedasticity, at which the null hypothesis of a 0 coefficient can be rejected. Asterisks denote significance at 10% or better. Weak instruments tests are *F*-statistics for the instruments in first-stage regressions. Overidentifying restrictions tests are chi-squared statistics; numbers in parentheses are probability levels for rejecting the null hypothesis that the excluded instruments are valid.

Table 8.—Panel Regressions Explaining Firm-Specific Stock Return Volatility: IPO Intensity

	Logarithm of Firm-Specific Volatility				Logarithm of Relative Firm-Specific Volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technological progress								
ln(*IT*)	0.120*	0.177*	0.198*	0.172*	0.113*	0.108*	0.115*	0.111*
	(0.000)	(0.003)	(0.000)	(0.003)	(0.009)	(0.015)	(0.008)	(0.013)
ln(*R&D*)		0.031*		0.033*		0.002		0.001
		(0.023)		(0.025)		(0.830)		(0.927)
IPO and corporate demography								
IPO10	−0.160	−0.415			−0.479	−0.420		
	(0.735)	(0.519)			(0.401)	(0.466)		
IPO20			0.156	0.247			−0.348*	−0.289*
			(0.381)	(0.368)			(0.006)	(0.033)
ln(*Size*)		−0.076		−0.086*		−0.042		−0.030
		(0.123)		(0.097)		(0.273)		(0.437)
Competition								
H		−1.346*		−1.299		0.275		0.261
		(0.098)		(0.132)		(0.436)		(0.436)
Systematic volatility								
$\ln(\sigma_s^2)$	0.240*	0.205*	0.236*	0.201*				
	(0.000)	(0.000)	(0.000)	(0.000)				
Adjusted R^2	0.816	0.823	0.817	0.824	0.582	0.582	0.583	0.583
Sample size	1,452	1,452	1,452	1,452	1,452	1,452	1,452	1,452

The dependent variables in columns 1 through 4 and 5 through 8 are, respectively, the logarithm of firm-specific stock return volatility and the logarithms of relative firm-specific stock return volatility. IPO intensity is defined as the market capitalization share of firms that listed no more than either ten (*IPO10*) or twenty (*IPO20*) years after their founding dates. Stock return volatility is defined as in table 1, and other explanatory variables are defined as in table 3. All explanatory variables are lagged by one year. All regressions include industry and time fixed effects. Observations are weighted by lagged total assets. The sample period is 1971 to 2006. The sample is a U.S. industry-year panel excluding the finance sector (SIC 6000–6999), industries with fewer than five firms, and industries for which explanatory variables are unavailable. Numbers in parentheses are probability levels for rejecting the null hypothesis of a 0 coefficient. Standard errors are clustered by industry, adjusting for heteroskedasticity and autocorrelation. Asterisks denote significance at 10% or better.

Differentiating these effects requires using cross-sectional variation, as in our panel regressions with industry and time fixed effects, or using long differences. A time trend toward younger listings is unlikely to drive the panel findings in table 4, which include time fixed effects that remove all time trends from the data. A time trend, if uniform across industries, is also unlikely to affect the long-difference regressions in table 5, for such a trend should merely shift the intercepts in these cross-sectional regressions. However, more nuanced age variables or a more complicated variation in IPO intensity across industries and through time might affect our findings.

We use founding-year-based IPO intensity variables as defined by Fink et al. (2005) to examine the impact of IPO on volatilities: the market-capitalization-weighted fraction of firms that listed within ten years of their foundings, denoted *IPO10*, and the fraction that listed within twenty years of their foundings, denoted *IPO20*. Founding years are obtained from the data sets used in Jovanovic and Rousseau (2001) and from the Web site of Jay Ritter.[18] Ritter's data cover IPOs from 1975 to 2008, and Jovanovic and Rousseau's (2001) data allow us to fill in early 1970s data.

Table 8 shows both *IPO10* and *IPO20* to be insignificant in explaining firm-specific stock return volatility. In columns 5 to 8, we use relative firm-specific stock return volatility as the dependent variable. Here, *IPO20* is significant but attracts the wrong sign. However, the sign and statistical significance of IT intensity itself remain unchanged across all specifications—again qualitatively similar results to those in table 4. Two-stage regressions, but also including either *IPO10* or *IPO20* as an additional explanatory variable, also generate results qualitatively similar to those shown in tables 6 and 7.

Overall, these robustness tests indicate that our finding linking IT intensity to firm-specific volatility is unlikely to be driven by changing IPO strategies.

C. Other Robustness Check

The results in tables 4, 5, 6, and 7 satisfy a battery of robustness checks. In describing each such check, we say the results are qualitatively similar if the signs, significance, and rough coefficient magnitudes of IT intensity are as in the tables.

Formal outlier analyses, using Cook's D statistics with the critical value of 1, confirm that our results are not driven by extreme observations. Observations in our regressions are weighted by industry sizes to compensate for potentially noisier observations of smaller industries. However, qualitatively similar results obtain from OLS regressions of firm-specific stock return volatility. Running our long-difference regressions of firm-specific TFP volatilities using OLS also generates qualitatively similar results if we drop small industries, defined as those whose weight represents less than 1% of our sample's aggregate assets. Using alternative weights, such as industry market capitalization or value-added, instead of industry assets also generates qualitatively similar results. Industries containing fewer firms might also generate noisier firm-specific volatility estimates, but weighting by the log of the number of firms in each industry

[18] We also use the average age of firms in an industry measured from the minimum of foundation or incorporation years, as discussed in Fink et al. (2005). Results are qualitatively similar to those of table 8.

also yields qualitatively similar results. Finally, including or excluding the two IT-producing industries generates qualitatively similar results.

We also consider additional controls. Firms' investment in a new GPT, and their complementary innovation activities, can require substantial upfront capital. Financially constrained firms might thus be prevented from adopting and adapting to new technologies like IT. We therefore include two additional control variables, leverage and liquidity, to proxy for financial constraints.[19] Each industry's firm size distribution is also considered, as another proxy for corporate demography, on the grounds that smaller firms are more likely to be financially constrained. Industry aggregate market-to-book ratios and advertising spending are considered proxies for the importance of intangible assets in an industry. We also include additional competition-related measures, first redefining deregulated industries to include electric and gas services and telephones only, on the grounds of their having undergone the most sweeping deregulation during the 1990s. Falling overall trade barriers increase the shares of imported goods in the United States and subsequently intensify price competition. To control for trade pressure on an industry, we use its import penetration ratio, defined as imports over total industry sales.[20] Since imports are available only for manufacturing industries, import penetration is 0 across all other sectors. We therefore always include a dummy variable for manufacturing industries alongside import penetration. Our findings are qualitatively robust to all these alternatives.

VI. Conclusion

Firm volatility dramatically increased in the final decades of twentieth century in the United States and then decreased, equally dramatically, in the first years of the twenty-first century, at least until the panic of 2008. The firm-specific component of firm volatility also grew more than its systematic component as firm-level volatility rose in the late twentieth century, and the firm-specific component fell faster than the systematic component as total firm-level volatility fell in the opening years of the new century. Overlaid on this time-series pattern, we observe a stable cross-industry relation between IT intensity and firm-specific volatility.

Our findings are consistent with IT, a new technology, propagating heterogeneously across firms at least initially and inducing a low-frequency volatility cycle. That is, we observe a period of enhanced heterogeneity in the late twentieth century, consistent with a broadened performance gap between winners and losers in sectors where investment in the new technology was more intense. This would occur if successful early adopters gleaned quasi-rents until imitators rose. We then observe firm heterogeneity reverting to 1970s levels in the early twenty-first century, consistent with Pastor and Veronesi (2009), who argue that IT diffusion was complete by 2002. Our finding of a stable cross-sectional relationship between firm heterogeneity and IT intensity throughout this cycle is consistent with the diffusion of the new technology as a primary driver of the pattern.

Our findings validate models of IT as a GPT that affects productivity across all sectors, not just those that developed the technology (Bresnahan & Trajtenberg, 1995; Helpman & Trajtenberg, 1998). Our findings evoke Schumpeter's (1912) creative destruction, wherein creative firms earn quasi-rents from their superior ability to ascertain best uses of the new technology as other firms fall behind, elevating firm-level heterogeneity for a time. Our findings are consistent with Chun et al. (2008), who find more IT-intensive industries exhibiting both more elevated firm-specific volatility and faster growth rates and forecast a reversal of this elevation once the GPT was fully incorporated into all sectors of the economy; with Comin et al. (2009) and Pastor and Veronesi (2009), who model changes in stock return volatility associated with the arrival of a new technology; and with Stiroh (2002), Basu and Fernald (2007), Oliner, Sichel, and Stiroh (2007), and others, who link faster aggregate TFP growth to efficiency gains from IT.

Creative destruction could underlie several peculiarities of the late twentieth century economy. Morck, Yeung, and Yu (2000) observe higher firm-specific volatilities in developed economies than developing economies and also document a rising firm-specific volatility in U.S. stock returns, the latter confirmed by Campbell et al. (2001). Fama and French (2004) link the latter to a surge of IPOs by young firms. Both the surge of new listings and their elevated firm-specific volatility could reflect intensified creative destruction; Hobijn and Jovanovic (2001) argue that new technology favors younger over established firms, and Jovanovic and Rousseau (2001) model a new GPT allowing firms to list earlier. Technological innovation might be tied to the intensified competition that Philippon (2003), Gaspar and Massa (2006), and Irvine and Pontiff (2009) detect in the late twentieth century. More intensive creative destruction in more developed economies might explain the initial finding of Morck et al. (2000).

Our findings suggest that the argument of Brandt et al. (2010) that the upsurge in firm volatility, which Morck et al. (2000), Campbell et al. (2001), Comin and Philippon (2005), and others document in the late twentieth centuries an episode of speculative trading by uninformed investors, cannot be a complete explanation. Rather, our findings reaffirm and extend the general thesis of Comin and Mulani (2007) that these patterns reflect technological change.

If we are correct in attributing the rise and fall of firm-specific volatility in the late twentieth and early twenty-first

[19] The average financial leverage of firms in each industry is defined as industry aggregate short- and long-term debt over industry aggregate assets (summed Compustat items 9 plus 34 over 6). The average financial liquidity of firms in each industry is defined as industry aggregate current assets over current liabilities (summed Compustat items 4 over 5).

[20] We follow Irvine and Pontiff (2009) in using National Bureau of Economic Research data. See Feenstra, Romalis, and Schott (2002).

centuries to phases in the propagation of IT, the latter phase should represent resumption of a steady state. Absent the elevated performance differences between winners and losers due to IT-related quasi-rents, firm volatility could still wax and wane, and isolated bouts of creative destruction in specific industries might create industry-specific episodes of elevated firm-specific volatility. But firm-level volatility should be more systematic and less firm specific than in the late twentieth century—at least until the next GPT.

REFERENCES

Acemoglu, Daron, "Comment: Diego Comin and Thomas Philippon, The Rise in Firm-Level Volatility: Causes and Consequences" (pp. 203–215), in Mark Gertler and Kenneth Rogoff (Eds.), *NBER Macroeconomics Annual*, vol. 20 (Cambridge, MA: MIT Press, 2005).

Basu, Susanto, and John G. Fernald, "Returns to Scale in U.S. Production: Estimates and Implications," *Journal of Political Economy* 105:2 (1997), 249–283.

——— "Information and Communications Technology as a General-Purpose Technology: Evidence from U.S. Industry Data," *German Economic Review* 8:2 (2007), 146–173.

Bennett, James A., and Richard W. Sias, "Why Company-Specific Risk Changes over Time," *Financial Analysts Journal* 62:5 (2006), 89–100.

Brandt, Michael W., Alon Brav, John R. Graham, and Alok Kumar, "The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episodes?" *Review of Financial Studies* 23:2 (2010), 863–899.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt, "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *Quarterly Journal of Economics* 117:1 (2002), 339–376.

Bresnahan, Timothy F., and Manuel Trajtenberg, "General Purpose Technologies: Engine of Growth?" *Journal of Econometrics* 65:1 (1995), 83–108.

Brown, Jeffrey R., and Austan Goolsbee, "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry," *Journal of Political Economy* 110:3 (2002), 481–507.

Brynjolfsson, Erik, Lorin Hitt, and Shinkyu Yang, "Intangibles Assets: Computers and Organizational Capital," *Brookings Papers on Economic Activity* 1 (2002), 137–198.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance* 56:1 (2001), 1–43.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, "The Stock Market Valuation of Research and Development Expenditures," *Journal of Finance* 56:6 (2001), 2431–2456.

Chun, Hyunbae, Jung-Wook Kim, Randall Morck, and Bernard Yeung, "Creative Destruction and Firm-Specific Performance Heterogeneity," *Journal of Financial Economics* 89:1 (2008), 109–135.

Chun, Hyunbae, and M. Ishaq Nadiri, "Decomposing Productivity Growth in the U.S. Computer Industry," this REVIEW 90:1 (2008), 174–180.

Comin, Diego, "An Uncertainty-Driven Theory of the Productivity Slowdown: Manufacturing," C. V. Starr Center for Applied Economics working paper no. 2000-16 (2000).

Comin, Diego, Mark Gertler, and Ana Maria Santacreu, "Technology Innovation and Diffusion as Sources of Output and Asset Price Fluctuations," NBER working paper no. 15029 (2009).

Comin, Diego, and Sunil Mulani, "Diverging Trends in Aggregate and Firm Volatility," *Review of Economics and Statistics* 88:2 (2006), 374–383.

——— "A Theory of Growth and Volatility at the Aggregate and Firm Level," Harvard University working paper (2007).

Comin, Diego, and Thomas Philippon, "The Rise in Firm-Level Volatility: Causes and Consequences" (pp. 167–201), in Mark Gertler and Kenneth Rogoff (Eds.), *NBER Macroeconomics Annual* (Cambridge, MA: MIT Press, 2005).

Davis, Steven J., John Haltiwanger, Ron Jarmin, and Javier Miranda, "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," NBER working paper no. 12354 (2006).

Fama, Eugene F., and Kenneth R. French, "New Lists: Fundamentals and Survival Rates," *Journal of Financial Economics* 73:2 (2004), 229–269.

Feenstra, Robert C., John Romalis, and Peter K. Schott, "U.S. Imports, Exports, and Tariff Data, 1989–2001," NBER working paper no. 9387 (2002).

Fink, Jason, Kristin Fink, Gustavo Grullon, and James Weston, "Firm Age and Fluctuations in Idiosyncratic Risk" (2005). http://ssrn.com/abstract=891173.

Franco, Francesco, and Thomas Philippon, "Firm and Aggregate Dynamics," this REVIEW 89:4 (2007), 587–600.

Fraumeni, Barbara M., "The Measurement of Depreciation in the U.S. National Income and Product Accounts," *Survey of Current Business* 77:7 (1997), 7–23.

Gaspar, Jose-Miguel, and Massimo Massa, "Idiosyncratic Volatility and Product Market Competition," *Journal of Business* 79:6 (2006), 3125–3152.

Griliches, Zvi, "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica* 25:4 (1957), 501–522.

Griliches, Zvi, and Jerry A. Hausman, "Errors in Variables in Panel Data," *Journal of Econometrics* 31:1 (1986), 93–118.

Hall, Robert E., "The Relationship between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy* 96:5 (1988), 921–947.

Hayek, Friedrich, *The Pure Theory of Capital* (Chicago: University of Chicago Press, 1941).

Helpman, Elhanan, and Manuel Trajtenberg, "A Time to Sow and a Time to Reap: Growth Based on General Purpose Technologies" (pp. 55–83), in Elhanan Helpman (Ed.), *General Purpose Technologies and Economic Growth* (Cambridge, MA: MIT Press, 1998).

Hobijn, Bart, and Boyan Jovanovic, "The Information-Technology Revolution and the Stock Market: Evidence," *American Economic Review* 91:5 (2001), 1203–1220.

Irvine, Paul, and Jeffrey Pontiff, "Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition," *Review of Financial Studies* 22:3 (2009), 1149–1177.

Jin, Li, and Stewart Myers, "R-Squared around the World: New Theory and New Tests," *Journal of Financial Economics* 79:2 (2006), 257–292.

Jovanovic, Boyan, and Peter L. Rousseau, "Why Wait? A Century of Life before IPO," *American Economic Review* 91:2 (2001), 336–341.

——— "General Purpose Technologies" (pp. 1181–1224), in Philippe Aghion and Steven Durlauf (Eds.), *Handbook of Economic Growth* (Amsterdam: Elsevier, 2005).

Li, Kan, Randall Morck, Fan Yang, and Bernard Yeung, "Firm-Specific Variation and Openness in Emerging Markets," this REVIEW 86:3 (2004), 658–669.

Morck, Randall, Bernard Yeung, and Wayne Yu, "The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movement?" *Journal of Financial Economics* 58:1 (2000), 31–48.

Oliner, Stephen D., Daniel E. Sichel, and Kevin J. Stiroh, "Explaining a Productive Decade," *Brookings Papers on Economic Activity* 38:1 (2007), 81–152.

Olson, Mancur, *The Logic of Collective Action: Public Goods and the Theory of Groups* (Cambridge, MA: Harvard University Press, 1971).

Parker, Miles, "Diverging Trends in Aggregate and Firm-Level Volatility in the UK," Bank of England External Unit MPC discussion paper no. 16 (2006).

Pastor, Lubos, and Pietro Veronesi, "Stock Valuation and Learning about Profitability," *Journal of Finance* 58:5 (2003), 1749–1790.

——— "Technological Revolutions and Stock Prices," *American Economic Review* 99:4 (2009), 1451–1483.

Petersen, Mitchell A., "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," *Review of Financial Studies* 22:1 (2009), 435–480.

Philippon, Thomas, "An Explanation for the Joint Evolution of Firm and Aggregate Volatility," New York University working paper (2003).
Schumpeter, Joseph, *Theorie der wirtschaftlichen Entwicklung* (Leipzig: Dunker und Humbolt, 1912).
——— *Business Cycles* (New York: McGraw-Hill, 1939).
Stiroh, Kevin J., "Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say?" *American Economic Review* 92:5 (2002), 1559–1576.
Stock, James H., and Motohiro Yogo, "Testing for Weak Instruments in Linear IV Regression" (pp. 80–108), in Donald W. K. Andrews and James H. Stock (Eds.), *Identification and Inference in Econometric Models: Essays in Honor of Thomas J. Rothenberg* (Cambridge: Cambridge University Press, 2005).
Thesmar, David, and Mathias Thoenig, "Financial Market Development and the Rise in Firm Level Uncertainty," CEPR discussion paper no. 4761 (2004).
U.S. Bureau of Labor Statistics, *BLS Handbook of Methods* (Washington, DC: Bureau of Labor Statistics, 1997).
Wei, Steven X., and Chu Zhang, "Why Did Individual Stocks Become More Volatile?" *Journal of Business* 79:1 (2006), 259–292.
Winston, Clifford, "U.S. Industry Adjustment to Economic Deregulation," *Journal of Economic Perspectives* 12:3 (1998), 89–110.