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Increased Heterogeneity among U.S. Firms: Facts and Implications

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Abstract

The firm-level volatility of the output growth of publicly listed U.S. firms rises through the latter 20th century, even as their aggregate output growth volatility falls. Decomposing shocks to firms into economy-wide, industry-wide, and firm-specific components explains this fallacy of composition. The importance of firm-specific shocks rises steadily relative to the others, reducing cross-sectional correlations between firms' growth rates. Across industries and over time, firm-specific output growth volatility rises with firm-specific volatility in total factor productivity (TFP) growth, more than in capital or labor growth rates. Elevated firm-specific TFP growth volatility tracks information technology (IT) capital accumulation, rather than other changes in the business landscape. We hypothesize that shocks to U.S. firms changed qualitatively, becoming more firm-specific as productivity gains from this new general purpose technology, IT, accrued to specific innovative firms, rather than evenly across all the firms in whole industries or the whole economy, at least in these early decades of its absorption. If so, the so-called Great Moderation in U.S. GDP growth volatility may be, in part at least, a temporary artifact of technology driven heterogeneity across firms.

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1. Introduction

Firm-level volatility of publicly listed firms in the U.S. rises in the latter 20th century alongside falling aggregate volatility in total corporate sector sales, and the total market capitalization of all listed firms (Morck *et al*., 2000; Campbell *et al*., 2001; Comin and Philippon, 2005; Comin and Mulani, 2006; Chun *et al*., 2008).[1]

This fallacy of composition in volatility is intuitively straightforward. Firm-level growth is decomposed into a *systematic component*, related to industry or market fluctuations, and a residual or *firm-specific component*, which has zero mean across firms and thus cancels out in the aggregate. If average firm-level volatility rises, with its firm-specific component rising faster than its systematic component the decreasingly correlated firm-level shocks coalesce into a falling aggregate volatility (Morck *et al*., 2000; Campbell *et al*., 2001).

This implies a qualitative change in the shocks affecting listed U.S. firms. Shocks shared by all firms in an industry or in the economy wane in the late 20th century, while shocks specific to individual firms wax dominant. Listed firms comprise about half of aggregate value-added and 95% of private R&D (Comin and Mulani, 2007), so the causes and consequences of this qualitative change merit investigation.

To this end, we perform a two-stage decomposition of firm-level output growth. First, we decompose the output growth rate of each U.S. firm in Compustat into components associated with growth in its labor and capital employed plus a residual, taken to be total factor productivity (TFP) growth. Second, we estimate the volatilities of the output, labor, capital, and TFP growth for each firm in each industry, and decompose each volatility into systematic (correlated with industry- or economy-wide fluctuations) and firm-specific (uncorrelated with such fluctuations) components, which we average across all firms in that industry. For each industry, we thus obtain eight volatility measures: systematic and firm-specific volatilities of output, labor, capital, and TFP growth rates from 1971 to 2000. These volatility measures let us relate rising firm-specific output growth volatility to rising firm-specific

[1] Increased firm-level volatility of publicly listed firms' sales growth is not confined to the U.S. and is also observed in France (Thesmar and Thoenig, 2004) and in the U.K. (Parker, 2006).

volatility in input and productivity growth rates.

Elevated firm-specific volatility in input growth is plausible for a variety of reasons. Veldkamp and Wolfers (2007) argue that firms' costs of obtaining information about their specific market situations fell in recent decades, rendering input decision based on firm-specific information increasingly cost-effective relative to using aggregate information. Such a change in the relative prices of different sorts of information could, ceteris paribus, elevate firm-specific factor price volatility. Moreover, if U.S. input markets grew nimbler over time, and thus more accommodating of firms' idiosyncratic fluctuations in factor demand, rising firm-specific volatility in factor prices ensues even if the relative prices of various sorts of information remain unchanged.

The U.S. labor market does appear increasingly efficient at matching employees to jobs (Stiroh, 2006). Katz and Krueger (1999) estimate *Beveridge curves*, plots of job vacancies against unemployment rates, for the U.S. in the mid-1980s and the 1990s. The curve shifts down – with fewer vacancies at each unemployment rate. This is consistent with the unemployed spending less time between jobs, and thus with more efficient matching. Firms also increasingly hire short-term employees, who move from firm to firm easily (Autor, 2003). Further flexibility may arise from declining unionization and falling union wage premiums, with previously heavily regulated industries especially likely to exhibit changes of these sorts (Hirsch, 1988; Peoples, 1998; Hirsch and Macpherson, 2000).[2]

The U.S. financial system also evolved rapidly in the late 20th century, perhaps increasing its precision in directing capital to its best uses. Financial development, precise capital allocation, and elevated firm-specific stock return volatility are all interlinked (Wurgler, 2000; Durnev *et al*., 2004; Thesmar and Theonig, 2004), and the last rises markedly in the U.S. in recent decades (Morck *et al*., 2000; Campbell *et al*., 2001). Successive waves of financial deregulation arguably sharpen competition in financial intermediation (Calomiris, 2000). Large databases arguably improve the quality of credit

[2] Six industries (excluding financial industries) qualify as 'deregulated' – transportation (railroad, trucking, and transportation by air), telephone, electric and gas services, and motion pictures. For details, see Winston (1998).

allocation (Evans and Wurster, 1997; Passmore and Sparks, 2000), and securities offerings (Wilhelm, 1999, 2001; Hauswald and Marquez, 2003).

But elevated firm-specific TFP growth volatility is also a plausible explanation for several reasons. Different firms might have different capabilities in applying new technology (Schumpeter, 1912). Hobijn and Jovanovic (2001), Jovanovic and Rousseau (2001), and others deduce a wave of intensified creative destruction redounding through the U.S. economy, as new and old firms in every industry race to find better uses for a new *general purpose technology* (GPT), *information technology* (IT), introduced into the U.S. economy in the late 20th century.[3] Successful adopters of the GPT possess complementary inputs, notably skilled labor and appropriate organizational forms (Bresnahan *et al*., 2002; Brynjolfsson and Hitt, 2003). However the distribution of these complements is not uniform across firms. Successful IT adoption permits new products, rising product quality, and improved timeliness (Kahn *et al*., 2001; Athey and Stern, 2002), which allow IT intensive firms to appropriate quasirents. These firms prosper by creating new uses of IT while others are destroyed, partially or even completely, increasing heterogeneity across firms, at least at the early stage of the technology's diffusion.[4] Alternatively, a growing proportion of unstable small and/or new firms might elevate the typical firm's TFP growth volatility (Pastor and Veronesi, 2003; Fama and French, 2004). Or, heightened competition from deregulation or globalization might magnify brief advances or snags into sustained TFP acceleration or retardation (Philippon, 2003; Irvine and Pontiff, 2005; Gaspar and Massa, 2006).

Consistent with all the above explanations, we find firms' output, input, and productivity growth rates are all affected increasingly by shocks unique to each specific firm. This change is most pronounced for TFP growth rates, whose rise in firm-specific volatility outpaces those of labor and capital, but closely tracks that of output growth rates.

We then use a cross-industry analysis to explore various explanations for this rising firm-specific

[3] Helpman and Trajtenberg (1998) define a GPT as a technology that transforms the way firms conduct business in general. One example is electrification in the early 20th century.
[4] Comparing diffusion patterns of IT and electrification across industries, Jovanovic and Rousseau (2005) show that IT diffused more slowly. From 1960 through 2001, cross-industry variation of IT declined, but remains substantial.

TFP growth volatility – technological progress, enhanced domestic competition, globalization, and others. Long-difference regression of firm-specific TFP growth volatility increases on proxies for these explanations leave only information technology consistently significant – implicating differing firm-level capabilities in applying that technology.[5]

Our findings validate models of IT as a GPT that affects productivity across all sectors, not just those that developed the technology (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998). Our findings are consistent with Schumpeter's (1912) creative destruction, wherein creative firms destroy, partially at least, technology laggards; magnifying the dispersion of TFP growth rates observed across firms in each affected industry.

Our findings also point to an economic explanation for recent findings of rising firm-specific volatility in stock returns (Morck *et al*., 2000; Campbell *et al*., 2001), accounting returns (Wei and Zhang, 2006), and sales and employment growth (Comin and Mulani, 2006) by demonstrating an underlying rise in firm-specific TFP growth volatility. We also find that industries with high turnover rates of top ranking firms exhibit high firm-specific TFP growth volatility, consistent with the hypothesis that the dethroning of corporate behemoths by creative innovators underlies economic growth, as discussed in Fogel *et al*. (2008).

They also illuminate the ostensible *Great Moderation* in GDP growth volatility (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001).[6] Although in no way undermining other explanations, like declining firm-level volatility due to improved supply chain management, most notably in the durable good sector (Kahn *et al*., 2001; Davis and Kahn, 2007);[7] falling volatility among unlisted firms (Davis *et al*., 2006); or decreasing correlations across industry aggregate data (Comin and Philippon, 2005; Irvine and Schuh, 2005, 2007); our findings underscore the likely first order importance of intensified creative destruction, at least in the early decades of the absorption of a

[5] Following Griliches and Hausman (1986), we use the term 'long-difference' to describe differencing the data more than one period apart – in this case using increases in decade averages from the 1970s to the 1990s. See Section 3 for more detail.
[6] Volatilities of other macroeconomic variables, such as inflation and unemployment rates, exhibit similar patterns (Stock and Watson, 2002).
[7] Our two-digit industry classification includes 10 durable manufacturing industries – primary metals, transportation equipment, etc.

new GPT into the economy in the late 20th century, rendering shocks to individual firms increasingly firm-specific, and thus increasingly prone to cancel out in the aggregate. Increased firm-specific volatility also underlies and augments falling correlations across sectors in attenuating GDP growth volatility.

This suggests potentially fruitful new avenues for real business cycle (RBC) research in exploring conditions that magnify idiosyncratic technology shocks yet attenuate macroeconomic business cycles (Hansen *et al*., 2006).

This paper is structured as follows. Section 2 explains our data and variables. Section 3 describes the basic trends in the variables. Section 4 examines possible determinants of firm-specific TFP growth volatility and Section 5 summarizes our conclusions and elaborates on their implications.

2. Data and Variables

Our firms-specific volatility variables are constructed via a series of volatility decompositions. This section describes these decompositions in detail.

We first decompose output growth rates into input (labor and capital) growth rates and a residual we take as TFP growth. This gives us four firm-level growth rates – in output, labor, capital, and TFP – for each firm each year. We then estimate the volatilities of these growth rates through successive ten-year rolling windows for each firm; and decompose each volatility into *systematic* components, correlated with industry or market fluctuations, and a residual *firm-specific* (idiosyncratic) volatility. We average these across all the firms in each industry, obtaining an annual panel of eight industry-level variables: firm-specific and systematic volatilities in the growth rates of each of output, labor, capital, and TFP.

Note that this decomposition differs from recent work in macroeconomics, which compares firm-level and macroeconomic variables. In this paper, *firm-specific* volatility means firm-level volatility unrelated to industry- or economy-wide fluctuations, not simply firm-level volatility; and *systematic* volatility means firm-level volatility that *is* related to industry- or economy-wide fluctuations.

2.1 Decomposing Output Growth into Input and TFP Growth

We measure firm output as *real value-added*, denoted $Y_{j,t}$, with j and t firm and time subscripts, respectively. This 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* data to construct substitutes.[8] Our output growth rate is then

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

The input factors are *labor force*, $L_{j,t}$, the firm's employee count (Compustat item 29) and *real capital stock*, $K_{j,t}$, its net property, plant and equipment (PP&E) (item 8) deflated, as in Hall (1990), to reflect the average age of these assets. Asset age is approximated as balance sheet depreciation (items 7 minus 8) over income statement depreciation and amortization (item 14). Outliers are mitigated by taking a five-year moving average and defining the average age of firm j's assets at time t, $a_{j,t}$, as the minimum of this moving average and 20. Taking all of firm j's assets as $a_{j,t}$ years old, we deflate their PP&E with the BEA *Fixed Reproducible Tangible Wealth* (FRTW) industry-level deflator to estimate the firm's real capital stock. We call the result the firm's real capital stock, $K_{j,t}$. Growth in labor and capital are then $g(L_{j,t})$ and $g(K_{j,t})$, with $g(\cdot)$ is defined as in [1].

TFP growth, $g(TFP_{j,t})$, is output growth unaccounted for by growth in capital or labor employed, defined as

[8] Our sample ends in 2000, the last year BEA and BLS report most SIC-based industry-level data. Newly introduced NAICS-based data are only available from 1987. Since we use Compustat data from 1961, we use SIC-based data.

[2] $$g(TFP_{j,t}) \equiv g(Y_{j,t}) - \frac{1}{2}(S_{L,j,t} + S_{L,j,t-1})g(L_{j,t}) - \frac{1}{2}(S_{K,j,t} + S_{K,j,t-1})g(K_{j,t})$$

where $S_{L,j,t}$ and $S_{K,j,t}$ are the firm's labor and capital cost shares, respectively.[9] The labor cost share, $S_{L,j,t}$, is labor and related expenses (item 42 or the estimate described below) divided by this 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 industry-level ratio of benefits to total compensation, from GPO data. Capital services cost is defined as capital assets, $K_{j,t}$, times industry $i(j)$'s annual rental price of capital. To estimate the last, we use FRTW data on the asset composition of each industry each year to aggregate BLS asset-specific rental prices of capital, tax-adjusted as in BLS (1997), using the Törnqvist method. Firm j's capital cost share, $S_{K,j,t}$, is one minus its labor cost share.

2.2 Decomposing Firm-Level Volatilities into Firm-Specific and Systematic Components

We now decompose the volatilities of the growth rates constructed above into firm-specific and systematic components.

Growth Rate Volatilities

We first calculate the total volatilities of each firm's growth rates in output, labor, capital, and TFP through time. For each firm j, these are the simple time series variances of $g(Y_{j,t})$, $g(L_{j,t})$, $g(K_{j,t})$, and $g(TFP_{j,t})$, each calculated over a ten-year rolling window ending in year t. Since Compustat includes only

[9] This technique imposes neither constant returns to scale nor zero economic profits. See Hall (1988) and Basu and Fernald (1997) for details on the construction of TFP measures.

publicly held firms, and we exclude financial firms, our aggregates differ from BLS aggregate growth rates. The average annual TFP growth rate for our publicly held firms is higher than for BLS data. However, our aggregate annual TFP growth rates correlate highly with those provided by the BLS (ρ=0.6). Further, as Figure A in the Appendix shows, the two volatility measures exhibit a very similar pattern.

Decomposition of Growth Rate Volatilities

The next step decomposes the volatility of each firm-level growth rate into firm-specific and systematic components by year and averages these across each industry. To do this, we first regress firm *j*'s output growth rate on the output growth rate of the firm's primary industry *i*(*j*), $\overline{g}_{i(j)}(Y_{j,t})$, and on the output growth rate of the economy, $\overline{g}(Y_{j,t})$, over a ten-year rolling window ending in year t.[10] That is, we regress

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

over the ten years $\tau \in [t-9,\ t]$. $\overline{g}_{i(j)}(Y_{j,\tau})$ is the value-added-weighted sum of the growth rates of all *other* firms in the industry. $\overline{g}(Y_{j,\tau})$ is the value-added-weighted sum of the growth rates of all other firms in all industries. Note that these industry and market indexes are different for each firm because they always exclude firm *j* itself. This exclusion keeps 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 5 observations in the window.

Using this firm-level regression result, we define industry *i*'s *systematic output growth volatility* as

[10] Our two-digit level industry classification corresponds to that in the GPO and FRTW datasets, and contains 55 industries, with 20 in manufacturing. We exclude financial industries (SIC 6000 to 6999) and industries with fewer than 5 firms.

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

where $SSM(Y_{j,t})$ is the explained variation of regression [3] for firm j in industry i and $\sum_{j\in i} T_{j,t}$ is the number of annual observations available in industry i given an estimation window. Industry i's systematic labor, capital, and TFP growth volatilities are defined analogously as $\sigma^2_{s,i,t}(L)$, $\sigma^2_{s,i,t}(K)$, and $\sigma^2_{s,i,t}(TFP)$.

Firm-Specific Volatility

We next use the sum of squared variation in the residuals, $SSR(Y_{j,t})$, of regression [3] run on data for each firm j in each window $[t-9,\ t]$ to estimate its firm-specific output growth volatility. Using this, we define industry i's *firm-specific output growth volatility* as

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

Industry i's firm-specific labor, capital, and TFP growth volatilities are defined analogously as $\sigma^2_{\varepsilon,i,t}(L)$, $\sigma^2_{\varepsilon,i,t}(K)$, and $\sigma^2_{\varepsilon,i,t}(TFP)$.

An alternative ways of calculating firm-specific volatility is to measure it as a fraction of total volatility; that is, relative to systematic volatility. We define industry i's *relative firm-specific output growth volatility* as

$$[6] \qquad \psi_{i,t}(Y) \equiv \frac{1-R^2_{i,t}(Y)}{R^2_{i,t}(Y)} = \frac{\sigma^2_{\varepsilon,i,t}(Y)}{\sigma^2_{s,i,t}(Y)}$$

with $R^2_{i,t}$ the mean fraction of firm-level volatility in industry *i* explained by industry and market factors, defined as

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

Industry *i*'s relative firm-specific labor, capital, and TFP growth volatilities are defined analogously as $\psi_{i,t}(L)$, $\psi_{i,t}(K)$, and $\psi_{i,t}(TFP)$.

3. Firm-Specific Output, Input, and TFP Growth Volatilities

3.1 Summary Statistics

We first verify that our panel of industry-year volatilities displays the patterns detected in previous studies (Comin and Philippon, 2005; Comin and Mulani, 2006). The total heights of the bars in Panel A of Figure 1 measure firm-level output growth volatility each year, averaged across industries weighted by value-added of the prior year. A clear increase over time is also evident in our data. Panel B of Figure 1 plots the time series of aggregate output growth volatilities constructed using the publicly held firms in our sample over ten-year rolling windows ending in the designated years.[11] This exhibits a pattern similar to that of aggregate GDP growth volatility, which falls substantially after the mid-1980s (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001), indicating a widening divergence between firm-level and aggregate volatility for publicly held firms.

[Figure 1 and Table 1 about here]

Panel A of Table 1 reports summary statistics for the annualized expansion rates of our firm-

[11] We first calculate value-added-weighted sum of growth rates of all firms in Compustat, then estimate volatilities in these growth rates using ten-year rolling windows.

specific volatility measures.[12] Annualized volatility expansion rates are defined as follows. We first calculate the decade averages of firm-specific volatilities of output growth rates for the 1970s and for the 1990s; and then define the long-difference (Griliches and Hausman, 1986) in volatility for each industry *i* as [13]

$$[8] \qquad \Delta \ln\left[\sigma^2_{\varepsilon,i}(Y)\right] \equiv \ln\left[\bar{\sigma}^2_{\varepsilon,i,t}(Y)\right]_{t\in 1990s} - \ln\left[\bar{\sigma}^2_{\varepsilon,i,t}(Y)\right]_{t\in 1970s}.$$

This increase occurs over two decades; so dividing our long-difference by twenty provides an annualized expansion rate, $g\left(\sigma^2_{\varepsilon,i}(Y)\right)$, for the industry's firm-specific output growth volatility. We average these expansion rates across industries, weighting by industry average value-added in the 1970s. Annualized expansion rates in firm-specific labor, capital, and TFP growth volatilities are defined analogously, and denoted $g\left(\sigma^2_{\varepsilon,i}(L)\right)$, $g\left(\sigma^2_{\varepsilon,i}(K)\right)$, and $g\left(\sigma^2_{\varepsilon,i}(TFP)\right)$, respectively. Annualized expansion rates in relative firm-specific volatility measures are also calculated, and denoted by $g\left(\psi_i(Y)\right)$, $g\left(\psi_i(L)\right)$, $g\left(\psi_i(K)\right)$, and $g\left(\psi_i(TFP)\right)$ for output, labor, capital, and TFP growth, respectively.

Several interesting patterns emerge. First, Panel A of Table 1 shows the annualized expansion of firm-specific output growth volatility (6.05%) exceeds those for labor (3.42%) and capital (4.11%), but is similar to that for TFP (6.83%).[14] Expanding firm-specific input growth volatilities suggest that input markets may well have become more efficient and flexible (Katz and Krueger, 1999; Autor, 2003; Durnev *et al.*, 2004; Stiroh, 2006) in incorporating firm-specific information relative to aggregate information (Veldkamp and Wolfers, 2007). However, the much larger increase in firm-specific TFP

[12] We use the term *expansion rate*, rather than growth rate, to gauge increases in volatilities over time because we analyze the changing volatilities of growth rates in output, inputs, and productivity. This lets us avoid discussing "growth rates in growth rates' volatilities" and correctly evokes the intuition of rising volatility as a broadening of the probability distribution of the underlying growth rate components.

[13] Our findings are robust to various windows. For example, McConnell and Perez-Quiros (2000) argue 1984 to be a structural break in key macroeconomic time series. Similar patterns of rising firm-specific volatility are also evident from before to after 1984.

[14] All weighted average expansion rates in Panel A of Table 1 are statistically different from zero at the 5% level or better.

growth volatility relative to firm-specific input growth volatilities suggests a structural change in the nature of technological innovation underlying the patterns we identify in firm-specific output growth volatility – and perhaps those we detect in firm-specific input growth volatilities as well, since input decisions are partly driven by changes in TFP. Second, similar patterns are found in the annualized expansions of the relative firm-specific volatilities. The relative firm-specific output growth volatility expands at an annualized clip of 1.49%, outpacing that in labor (0.51%) or capital (1.18%), but paralleling that in TFP (1.61%). The significant positive expansions in relative firm-specific volatilities suggest a faster increase in the firm-specific component of firm-level volatility than in its systematic component. This again recalls the increased divergence between firm-level and aggregate volatilities reflecting increased heterogeneity across firms, or decreased pairwise correlations between firms' growth rates. in the latter part of the sample period.[15]

Panel B of Table 1 contrasts the annualized expansion in firm-specific TFP and input growth volatilities. We first calculate the differences between two volatility expansion rates for each industry, and then average these differences across industries, weighted by industry mean value-added in the 1970s. A pattern similar to that in Panel A of Table 1 emerges.

[Figure 2 and 3 about here]

Figure 2 shows the underlying data used to calculate Table 1. Panel A of Figure 2 plots the firm-specific output, input, and TFP growth volatilities each year. Panel B of Figure 2 plots yearly ratios of firm-specific TFP growth volatility over firm-specific input growth volatility (grey for labor and black for capital), highlighting the mounting importance of firm-specific TFP growth volatility relative to firm-specific input growth volatilities.

Figure 3 sorts industries by their annualized expansions in the firm-specific output growth volatility to illustrate cross-industry variation in these and the other firm-specific volatility expansion

[15] Section 3.2 discusses the relationship between average firm-specific volatility and average correlation.

rates we estimate.[16] Four of the ten industries posting the greatest expansions in firm-specific output growth volatility are in manufacturing. Two, electric and gas services and telephones, are recently deregulated; and two are "high tech," chemicals (including pharmaceuticals) and industrial machinery. Oil extraction also ranks in the top ten. However, a wide range of industries exhibit escalating firm-specific volatility too, clearly indicating that the phenomenon is not restricted to a few sectors. Figure 3 also exhibits a pattern which is broadly consistent with the finding of Table 1 in that industries which exhibit more rapidly expanding firm-specific output growth volatility tend to exhibit greater expansions in firm-specific TFP growth volatility, rather than in firm-specific input growth volatilities.

To sum up: we detect a qualitative change in the nature of shocks from the 1970s to the 1990s: shocks solely to individual firms wax more important as shocks shared by all the firms in an industry and shocks spread across all firms in the economy wane. Economic shocks grow more idiosyncratic over time.

3.2 Decreasing Correlations across Firms

The business cycle is, by definition, a macroeconomic phenomenon – characterized by extensive comovement across firms. On average, firms grow together during a boom and shrink together during a recession. However, the volatility pattern identified in Panel A of Table 1 shows this positive correlation across firms becoming much weaker in recent decades. This section shows, using a simple framework, how escalating relative firm-specific volatility directly implies declining pairwise correlations across firms' growth rates.

Consider a simple framework where the growth rate of firm *j* in any industry *i* can be written as,

[16] In addition to expansion in firm-specific volatility measures, we did a further reality check on the level of volatility measures averaged across all years for each industry. Again, intuitively plausible patterns emerge. The industry most prone to firm-specific volatility in output, input, and productivity growths is motion pictures. Each motion picture company's output growth depends on the popularity of the films it releases, and a single runaway hit can dramatically boost ticket revenues. Likewise, a year of box office failures can dramatically erode revenues. The success or failure of each movie is thus an idiosyncratic and largely unpredictable event (see e.g., Caves, 2002). Consequently, we observe sample maximum firm-specific volatilities in all the growth rate measures in this sector. Natural resources sectors, like metal mining and oil extraction, also exhibit high firm-specific volatilities across the board. Again, striking gold or oil generates an entirely idiosyncratic spike in output growth, and calls for sharp increases in capital and labor use. Finally, sectors like industrial machinery, electronics, and business services in which innovation is critical to success also exhibit elevated firm-specific volatilities. Minimal firm-specific volatility is exhibited by regulated industries such as tobacco products, railroads, and electric and gas services. Among these regulated industries, industries experiencing deregulation such as electric and gas services exhibit more rapidly expanding firm-specific volatilities even though the average level of them in the 1990s is still very low.

[9] $$r_{j,t} = \beta_m \eta_{m,t} + \beta_i \eta_{i,t} + \varepsilon_{j,t}$$

with $\eta_{m,t}$, $\eta_{i,t}$, and $\varepsilon_{j,t}$ representing orthogonal market-wide, industry-wide, and firm-specific shocks, respectively. By construction, the $\eta_{i,t}$ average to zero across all industries; the $\varepsilon_{j,t}$ average to zero across all firms within each industry. We assume the firm-specific volatility, i.e., the volatility of $\varepsilon_{j,t}$, to be the same for all firms in an industry, and denote this volatility σ_ε^2. Similarly, the volatilities of $\eta_{m,t}$ and $\eta_{i,t}$ are denoted σ_m^2 and σ_i^2, respectively.

The pairwise correlation of the growth rates of firms *j* and *k*, both in industry *i*, is

[10] $$\rho_{j,k} = \frac{\beta_m^2 \sigma_m^2 + \beta_i^2 \sigma_i^2}{\beta_m^2 \sigma_m^2 + \beta_i^2 \sigma_i^2 + \sigma_\varepsilon^2} = \left(1 + \frac{\sigma_\varepsilon^2}{\sigma_s^2}\right)^{-1}$$

with systematic volatility defined as $\sigma_s^2 \equiv \beta_m^2 \sigma_m^2 + \beta_i^2 \sigma_i^2$. Equation [10] shows that the simple correlation of the growth rates of firms *j* and *k* is a inverse function of the ratio of firm-specific to systematic volatility. Thus, if firm-specific volatility escalates faster than systematic volatility, the average pairwise correlation falls. This framework is obviously simplistic, but nonetheless faithfully characterizes the link between pairwise correlation coefficients and firm-specific versus systematic volatility. Our estimation allows β_m and β_i to differ for each firm in an industry, and although this complicates the algebra in [10], the absolute value of the pairwise correlation coefficient remains a decreasing function of firm-specific volatility regardless of the magnitudes and signs of the betas.[17]

[17] If we let firms have different betas, the linkage between correlation coefficients and heterogeneity can become more subtle. For example, if firm A's beta is negative but firm B's is positive, the correlation coefficient of the firms' growth rates is negative. Elevated firm-specific volatility then *increases* this negative value closer to zero as the firms exhibit less collinear growth rates

[Figure 4 about here]

To gauge typical growth rate correlations, we randomly select 500 firms and list all possible pairs among them.[18] For each such pair of firms in each ten-year rolling window, we estimate four correlation coefficients – one each for their growth rates in output, labor, capital, and TFP. Figure 4 plots the average across all pairs of firms of these four correlation coefficients against time, measured by the endpoints of the ten-year rolling windows.

All four average pairwise correlation coefficients fall with time, consistent with the increasing importance of firm-specific component of firm-level volatility. Moreover, the average pairwise correlation of firm-level TFP growth rates falls more substantially than those of labor and capital growth rates. These findings thus align with those in Table 1, which shows the escalating firm-specific volatility of TFP growth most closely tracking that of output growth.

3.3 The Importance of Escalating Firm-Specific TFP Growth Volatility

The findings in the previous sections show similar expansions in the firm-specific volatilities of output and TFP growth rates; with both expanding more than the firm-specific volatilities of the inputs growth rates. Consistent with this, Table 2 shows stronger correlations between the firm-specific (or relative firm-specific) volatilities of output and TFP growth rates than between those of output and inputs growth rates.

[Table 2 about here]

This last observation suggests that we might examine the roles of escalating firm-specific

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and become more heterogeneous. Figure 4 shows typical correlation coefficients in our data to be positive and declining over time. Thus, the simplistic specification in [10] characterizes our data adequately.

[18] For each ten-year window, we randomly select 500 firms from those with five or more observations. This provides a rough consistency with the sample used in [3].

volatilities of TFP, labor, and capital growth rates in explaining increased firm-specific output growth volatility. A quick (and dirty) way of doing this is to regress the last on the trio of possible contributors. This regression has obvious endogeneity problems, but is nonetheless a useful first pass.[19] The estimated OLS coefficients, with robust p-levels in parentheses below each, are

$$\underset{}{g\left(\sigma^2_{\varepsilon,i}(Y)\right)} = \underset{(0.124)}{0.978} + \underset{(0.135)}{0.147}\ g\left(\sigma^2_{\varepsilon,i}(L)\right) + \underset{(0.850)}{0.014}\ g\left(\sigma^2_{\varepsilon,i}(K)\right) + \underset{(0.000)}{0.615}\ g\left(\sigma^2_{\varepsilon,i}(TFP)\right) + u_i \tag{11}$$

and the regression R^2 is 0.759. Clearly, the escalation in firm-specific TFP growth volatility tracks that in firm-specific output growth volatility across industries by far the most closely.

Since we wish to relate this analysis to aggregate data, [11] might better be run weighting industries by their importance to the economy as a whole. We therefore run a weighted least squares (WLS) regression, weighting observations by (predetermined) industry value-added, averaged across all years in the 1970s, and obtain

$$g\left(\sigma^2_{\varepsilon,i}(Y)\right) = \underset{(0.049)}{0.693} + \underset{(0.023)}{0.279}\ g\left(\sigma^2_{\varepsilon,i}(L)\right) + \underset{(0.079)}{0.098}\ g\left(\sigma^2_{\varepsilon,i}(K)\right) + \underset{(0.000)}{0.585}\ g\left(\sigma^2_{\varepsilon,i}(TFP)\right) + u_i \tag{12}$$

with an R^2 of 0.871. Again, the escalation in firm-specific TFP growth volatility tracks that in firm-specific output growth volatility across industries much more closely than do the firm-specific volatility escalations in either capital or labor growth rates. The overriding importance of rising firm-specific TFP growth volatility is clearly not an artifact of small industries.

[19] This regression is, at least, not of an accounting identity because its dependent and independent variables are annualized expansion rates of *firm-specific* output, input, and TFP growth *volatilities*, which need not be independent.

4. Underlying Economics

Although the regressions [11] and [12] are clearly beset by a litany of econometric woes – and cannot, for example, unambiguously resolve what causes what – Tables 1 and 2 and Figures 1, 2, and 3 reveal clear regularities in the data that require explanation, the predominant role of firm-specific volatility of TFP growth over those of input growths in explaining recent increase in firm-specific volatility of output growth. Given that we have no complete and well-specified model of these phenomena, rigorous identification is impracticable. We therefore examine the data more closely, seeking additional regularities that might illuminate the economic underpinnings of the findings in Section 3.

4.1 Possible Economic Underpinnings

We do this by constructing proxies for industry characteristics that might correlate with the firm-specific TFP growth volatility. We first consider factors directly related to new technologies (IT and R&D), and then other factors such as firm demography, and intensified domestic and global competition, which might also affect firm-specific TFP growth volatility as explained below.

New Information Technology

Much recent work – Bresnahan and Trajtenberg (1995), Helpman and Trajtenberg (1998), Jovanovic and Rousseau (2005), Chun *et al*. (2008), and others – argues that IT is a general purpose technology (GPT), like steam engines in the 19^{th} century and electrification in the early 20^{th} century, which induces a broad wave of innovation across the entire economy. A GPT thus differs from most innovations, which have application only in a single firm or industry.

A GPT can render firms more heterogeneous because some realize the productivity gains the new GPT offers more fully than others. The latter may lack essential skilled labor (Bresnahan *et al.*, 2002), organizational capital, or both (Brynjolfsson *et al.*, 2002). Established firms may confront higher costs of switching technologies (Hobijn and Jovanovic, 2001).[20] Schumpeter (1912) and Hayek (1941) argue that rare entrepreneurial skills are unevenly distributed across firms. For these and other reasons, a new GPT might induce highly firm-specific productivity changes.[21] Chun *et al*. (2008) advance these arguments in linking IT capital to elevated firm-specific stock return and sales growth volatilities.

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 2000.[22] 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

$$[13] \qquad K_{i,k,t} = (1 - \delta_k)K_{i,k,t\text{-}1} + I_{i,k,t}$$

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

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

$$[14] \qquad IT_{i,t} \equiv \frac{\sum_{k \in IT} K_{i,k,t}}{\sum_{k \notin IT} K_{i,k,t}}.$$

Chun *et al*. (2008) show IT capital intensity to be distributed broadly across industries, as expected of a

[20] Laitner and Stolyarov (2003) note that a new GPT renders old knowledge and capital obsolete.
[21] Previous studies, including Stiroh (2002), link higher IT-intensity to faster productivity growth after the late 1990s.
[22] Herman (2000) describes FRTW. Our sample resembles those of Hobijn and Jovanovic (2001) and Stiroh (2002). Fama and French (1997) partition manufacturing more finely and non-manufacturing more coarsely, with 28 and 20 categories, respectively.

GPT; and also show it rising through the decades we study.

Research and Development (R&D)

Another possible source of new technology is R&D – innovation whose returns are largely captured by the individual creative firms doing the R&D spending. Heavy R&D spenders might create new products or technologies that enhance their productivity growth rates, but wreak havoc on their less innovative competitors – elevating observed firm-specific TFP growth volatilities. Also, R&D intensive firms in fierce patent races either win or lose, with the winner owning the new productivity enhancing technology and the loser reaping little from its past R&D spending.

We therefore construct a measure of industry-level R&D capital from annual R&D spending (Compustat item 46) as in [13], but with a 20% depreciation rate and using the GDP deflator, as in Chan *et al*. (2001). Each industry's *R&D intensity* is its capitalized R&D over its PP&E (item 8), a ratio analogous to [14]. Unlike IT intensity, which is broadly distributed across industries, R&D is highly concentrated in high-tech industries. This bides against it explaining the economy-wide elevations in firm-specific TFP growth volatility we detect.

Corporate Demography

Our Compustat database is restricted to listed firms, and U.S. exchanges have grown markedly more accommodating to newer and smaller firms over the past decades (Pastor and Veronesi, 2003; Fama and French, 2004). Since young and small firms are plausibly riskier than old and well-established firms, escalating firm-specific volatility in output and TFP growth rates might reflect this changing demography of listed firms. New and small firms are more capable of very fast growth than already huge behemoths, but are also more likely to suffer bankruptcies and near death experiences. This suggests that an industry containing relatively younger or smaller firms might exhibit greater firm-specific volatility in various performance measures.

We measure a firm's age as the number of years since its first appearance in CRSP, and its size as its total sales. We define an industry's average firm age as the log of the average age of its firms, and an industry's average firm size as the log of the average sales of its firms.

While we interpret these variables primarily as reflecting financial development, manifest in the presence of small and new firms on U.S. exchanges and consequently in Compustat, an alternative explanation cannot be dismissed. Schumpeter (1912) argues that innovators must often set up new firms because old established firms seldom support radical innovations, and that these new firms must often list on stock exchanges because brilliant innovators rarely have wealthy families and need risk-tolerant external equity financing. Consequently, an increased prominence of small young firms in U.S. equity markets might also be a sign of enhanced innovation.

Intensified Domestic Competition

Escalating firm-specific TFP growth volatility might reflect intensified competition (Philippon, 2003; Irvine and Pontiff, 2005; Gaspar and Massa, 2006). Irvine and Pontiff (2005) model intensified price competition as magnifying small mistakes into disasters and small economic profits into lasting leads. To proxy for product market competition in each industry, we construct annual *Herfindahl-Hirschman index* based on the annual sales of all firms in that industry, as reported in Compustat.

Irvine and Pontiff (2005) further suggest that deregulation in the 1980s and early 1990s might magnify firm-specific volatilities by letting firms that were previously tightly constrained by regulators adopt new and differing strategies. Some of these proved more successful than others, and narrow leads or lags again rapidly grew into sustained dominance or deep problems, enhancing observed firm-specific volatilities in output and TFP growth rates. Therefore, we introduce the indicator variable, δ_{dereg}, which is equal to one for extensively deregulated industries, and zero for others. Deregulated industries are transportation (railroad, trucking, transportation by air), telephone, electric and gas services, and motion pictures sectors as defined in Winston (1998).[23]

[23] However, as Acemoglu (2005) points out, the concentrated effect of deregulation in a handful of industries portents against its explaining the economy-wide elevations in firm-specific volatility detected in the previous section.

Intensified Global Competition

It is plausible to think that trade shocks become more firm-specific in their impacts on U.S. firms for two reasons. Lenway *et al*. (1996) show U.S. trade and non-tariff barriers against foreign steel products growing more precisely targeted at protecting the specific products produced by those U.S. firms that invest most heavily in political lobbying. If this pattern extends to other product markets, trade shocks might well be growing more firm-specific, with more politically invested firms largely shielded from shocks that buffet other firms in their industries.

Falling trade barriers exposed U.S. firms to stiffer international competition in the 1990s than in the 1970s. Irvine and Pontiff (2005) also argue that reduced overall trade barriers intensify price competition, and that this too magnifies small errors or lucky flukes into enduring problems or boons.

Consistent with both, Li *et al*. (2004) report elevated firm-specific stock return volatility when countries open their stock markets more fully to foreign investors. This reasoning suggests comparing manufacturing and non-manufacturing industries, for the latter are arguably less vulnerable to foreign import pressure because physical goods are easier to trade than most services and so should be less subject to trade-related escalations of firm-specific volatility.

To proxy for the trade pressure felt by firms in an industry, we use its import penetration ratio, defined as imports over total industry sales.[24] Since (goods) imports are defined only for manufacturing industries, we include an indicator variable, δ_{nmfg}, that is set to one for non-manufacturing industries and zero otherwise.

Long-Differences

As with our volatility increases, we consider long-differences in these proposed explanatory variables. That is, we subtract the mean of each variable in the 1970s from its mean in the 1990s. Thus, we gauge

[24] We follow Irvine and Pontiff (2005) in using National Bureau of Economic Research data – see Feenstra *et al*. (2002).

industry *i*'s increase in the logarithm of IT intensity, denoted $\Delta\ln(IT_i)$, by its log of IT intensity averaged across the 1990s less the log of analogous average across the 1970; its increase in mean firm age, denoted $\Delta\ln(Age_i)$, by the log of its mean firm age averaged across the 1990s less the log of the analogous average across the 1970s; increase in its domestic competitive pressure, denoted ΔH_i, by its average *Herfindahl-Hirschman* index over the 1990s minus the analogous average over the 1970s; and so on.

The only variables not long-differenced in this manner are the dummy for deregulated industries, since this dummy already signifies a long-term difference in the intensity of regulation, and the non-manufacturing industries dummy, which is included here to complement the long-difference in import intensity, which is only available for manufacturing industries.

4.2 Summary Statistics and Simple Correlations

It is unlikely that new technologies, deregulation, and firm demographics are independent factors. New technologies might amplify price competition. For example, Brown and Goolsbee (2002) link Internet growth to declining term life insurance premiums, consistent with the lower search costs on the web stimulating price competition. Schumpeter (1912) argues that older, more established firms have more difficulty absorbing and applying a new technology, thus linking technological change to firm age statistics. 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. These considerations make separating the potential effects of technology, competition, and firm demography on TFP growth volatility tricky.

[Table 3 and 4 about here]

Tables 3 and 4 present summary statistics and pairwise correlation coefficients between the explanatory variables enumerated in Section 4.1. In fact, the correlations are not very high. For example, the increase in an industry's information technology intensity from the 1970s to the 1990s, $\Delta\ln(IT)$, is positively and significantly correlated only with the indicator variables for deregulated and non-manufacturing industries. Increased R&D intensity is negatively correlated only with the indicator for non-manufacturing industries.

We suspect these relatively low correlations reflect our use of long-differences, rather than levels; which likely mitigates multicollinearity problems. Despite this reassurance that multicollinearity is not likely to be a major problem, we run regressions first on one explanatory variable (with an intercept) at a time before including multiple explanatory variables in horserace regressions. In general, significance levels are preserved from bivariate to multivariate regressions.

4.3 Regressions Explaining Increased Firm-Specific TFP Growth Volatility

Our dependent variable is the increase in the log of firm-specific TFP growth volatility from its 1970s average to its 1990s average, as defined in [8] in Section 3.1. Thus, our long-difference regressions at the industry-level are of the form

[15] $$\Delta\ln[\sigma^2_{\varepsilon,i}(TFP)] = a + \sum b_m \cdot \Delta x_{m,i} + c\Delta\ln[\sigma^2_{s,i}(TFP)] + e_i$$

and

[16] $$\Delta\ln[\psi_i\,(TFP)] = a + \sum b_m \cdot \Delta x_{m,i} + e_i$$

where the $\{x_{m,i}\}$ are one, some or all of the $m \in [1,8]$ explanatory variables for industry i as defined in Section 4.1. Long-differencing, removes industry fixed effects.[25] Section 3.2, discusses how the pattern of comovement is related to the relative magnitudes of firm-specific and systematic volatilities. Using relative firm-specific volatility as the dependent variable in [16], *de facto* constrains the coefficient of systematic volatility in [15] to equal one. In this sense, [15] is a more flexible specification.

[25] To address endogeneity further, we also estimate long-difference regressions using an instrumental variable for IT intensity. See Section 4.5 for further discussion. .

In the regression analyses, we drop all IT-producing industries – industrial machinery including electronic computers and peripherals and business services including software – from the industries listed in Figure 3. We do this because we seek to understand the role of IT in inducing volatility across the whole economy, not just in the industries that produce this new technology. We also drop industries where explanatory variables are unavailable.[26] This leaves a cross-section of 33 industries for our primary regressions. We run WLS regressions on these data, weighting each industry observation by industry value-added averaged across the 1970s.

[Table 5 about here]

4.4 Regression Results

Panels A and B of Table 5 report coefficient estimates of [15] and [16], respectively; along with *p*-values based on heteroskedasticity-consistent standard errors. The results in both panels clearly link intensified IT use to escalated firm-specific TFP growth volatility. Increased IT intensity is positive and significant consistently, regardless of whether it stands alone or alongside the other variables. The other technology variable, R&D intensity, is uniformly insignificant.

Our proxies for changing firm demography, which measure increases in the incidence of younger or smaller listed firms in each industry, are also less impressive than increased IT intensity. Increased firm age is generally insignificant, and increased firm size is significant only in Panel A.

Effects associated with enhanced domestic or global competition are barely significant. Neither increasingly monopolistic industries, identified by rising Herfindahl indexes, nor industries subject to enhanced trade pressure, identified by rising import penetration, exhibits significantly expanded firm-specific TFP growth volatility in any specifications. The non-manufacturing dummy also fails to attract

[26] Among the 41 industries shown in Figure 3, IT intensity is unavailable for three – farm, metal mining, and non-metal mining – and R&D intensity is unavailable for another three – railroads, water transportation, and transportation services. Results from regressions with the maximum possible number of observations for each column in Table 5 yield similar patterns of signs, magnitudes, and statistical significance. Further, the missing industries are small and our regressions are weighted by industry size, so the economic and statistical significance of our results are unchanged.

significant coefficients in most specifications. But the deregulated industries dummy exhibits sporadic significance.

In summary, increased IT intensity is most robustly and significantly associated with escalated firm-specific TFP growth volatility. This is consistent with intensified IT investment revealing a wave of creative destruction coursing across the economy, as creative firms in traditional industries successfully apply the new technology to enhance their productivity and leave their industry rivals behind. The other possible explanations enumerated in Section 4.1 cannot be dismissed out of hand, but appear less prominent in explaining the expansion of firm-specific TFP growth volatility, at least in these industries and this period.

4.5 Robustness

A wide range of robustness tests generate results qualitatively similar to those shown in Table 5, by which we mean that increased IT intensity is positive and significant in all specifications and the other explanatory variables are intermittently significant, insignificant, or attract inconsistent or perverse signs.

[Figure 5 about here]

We first check for outliers problems. Panels A and B of Figure 5 plot firm-specific TFP growth volatility escalation from the 1970s to the 1990s against increased IT intensity from the 1970s to the 1990s.[27] A strong positive correlation is obvious, and no outliers are evident. Formal outlier analyses confirm that our results are not driven by extreme observations. Table 5 runs WLS regressions to compensate for potentially noisier observations of smaller industries. However, qualitatively similar results are obtained if we run OLS and drop industries whose weights represent less than one percent of our sample's aggregate value-added. Using alternative weights, such as industry total assets, also

[27] Since regression 5a.1 of Table 5 includes systematic volatility as a control variable, both firm-specific volatility and IT intensity in Panel A of Figure 5 are residuals from regressions of each variable on systematic volatility.

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 also yields qualitatively unchanged results.

To clarify the economics beneath the overarching importance of increased IT intensity, we must consider the issue of endogeneity between the regression errors and increased IT intensity. For example, intensified firm-specific TFP shocks might induce firms to increase their IT investment, perhaps in hopes of better managing business risks.[28] To assuage this concern, we employ an instrumental variable for long-differenced IT intensity: the long-differenced tax rate on IT. To estimate the IT tax rate, we use asset-specific tax parameters that affect the marginal rental price of capital, defined as $Tax_{k,t} \equiv (1-\zeta_{k,t} - u_t z_{k,t})/(1-u_t)$ for asset k at time t, with $\zeta_{k,t}$ the effective rate of the investment tax credit, u_t the corporate income tax rate, and $z_{k,t}$ the present value of a dollar of tax depreciation allowances. These variables are all from the BLS. Using the IT asset composition of each industry each year, we aggregate these IT tax parameters using the Törnqvist method. Our long-differenced IT tax rate estimate passes standard weak instruments test criteria, generating a first-stage F-statistic larger than 10 (Stock and Yogo, 2005). Two-stage least squares (2SLS) regressions reconfirm the significance of the IT intensity variable.

We also experiment with various additional controls. Firms' investment in a new GPT, and their complementary innovation activities, can require substantial up-front capital. Financially constrained firms might thus be prevented from adopting and adapting to new technologies like IT. We therefore add two additional control variables, leverage and liquidity, to proxy for financial constraints. 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 annual 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 annual items 4 over 5). Each industry's firm size distribution is also considered, as

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

another proxy for firm 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 as proxies for the importance of intangible assets in an industry. Finally, we define deregulated industries more narrowly as those having undergone substantial deregulation during the 1990s – utilities and telecommunications. Our findings are qualitatively robust to all these alternatives.

4.6 Firm Turnover and Stock Market Volatility

Comin and Philippon (2005) and Fogel *et al.* (2008) interpret faster turnover of a country's leading firms as a sign of faster creative destruction. If our hypothesis that elevated firm-specific TFP growth volatility indicates intensified creative destruction is valid, increases in turnover measures from the 1970s to the 1990s should correlate positively with increases in the firm-specific TFP growth volatility. Following Comin and Philippon (2005), we define the turnover rate of an industry to be the fraction of its top quintile firms that fall to lower quintiles within five years. The first two columns of Table 6 report WLS regressions showing these two variables to be strongly positively related, consistent with the turnover of an industry's top firms being driven by firm-specific TFP shocks.

[Table 6 about here]

Chun *et al*. (2008) posit that differences in the firm-specific stock return volatilities in different U.S. industries reflect differing intensities of creative destruction. Our hypothesized link between creative destruction and firm-specific TFP growth volatility suggests a positive correlation between increases in the firm-specific stock return volatility and the firm-specific TFP growth volatility from the 1970s to the 1990s. The third and fourth columns of Table 6 confirm this link, consistent with increasingly heterogeneous stock returns reflecting increasingly heterogeneous TFP growth rates.

5. Conclusions

Our findings suggest that the business cycle attenuation of recent decade (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001) does not imply a more stable business environment for all individual firms. Rather, we find increased performance heterogeneity among listed firms, which cancels out in the aggregate performance of all listed firms. This implies a qualitative change in the nature of economic shocks – they increasingly affect specific firms, rather than whole industries or the whole economy. Exploring this change yields several insights.

First, although elevated firm-specific output volatility reflects elevated firm-specific volatility in factor employment and TFP growth rates, this effect is most pronounced for TFP growth. This is consistent with Comin and Mulani's (2007) finding that U.S. firms invest decreasingly in general innovations and increasingly in firm-specific innovations. From the 1970s to the 1990s, firm-specific TFP growth volatility rises at an annualized clip of 6.83%,[29] outpacing the 3.42% and 4.11% figures for labor and capital, respectively, but nicely in step with the observed 6.05% annualized increase in firm-specific output growth volatility. Industry-level cross-sectional correlations corroborate this, linking rising firm-specific output growth volatility more tightly to rising firm-specific TFP growth volatility, than to rising firm-specific volatilities of either capital or labor growth rates.[30]

Second, our findings are consistent with the hypothesis of Veldkamp and Wolfers (2007) that firms use more firm-specific information relative to industry- or economy-level information in determining their business strategies and factor demands than in the past – possibly reflecting reduced costs of acquiring firm-specific information. Firms' input decisions are based on their forecasts for the future productivities of those inputs, so if firms use more firm-specific information in estimating productivities, and if input markets are flexible enough to accommodate this change, the resulting increasingly nuanced factor demand shifts should be evident in expanded firm-specific input growth

[29] Rapidly expanding firm-specific TFP growth volatility is consistent with attenuating aggregate technology shock (Hansen *et al.*, 2006) because firm-specific TFP shocks cancel out in the aggregate.
[30] Galí and Gambetti (2007) document an increasing importance of technology shocks and a decreasing importance of demand shocks in the declining U.S. aggregate output growth volatility.

volatilities. Our results are consistent with this, but further reveal an even greater expansion in firm-specific TFP growth volatility. This suggests that the analysis of Veldkamp and Wolfers (2007) might usefully be extended to encompass sources of expanding firm-specific TFP growth rate volatility, such as intensified innovation, as well of expanding firm-specific input growth rate volatilities, in explaining expanding firm-specific output growth rate volatility.

Our findings also point to an economic explanation for recent findings of rising firm-specific volatility in stock returns (Morck *et al*., 2000; Campbell *et al*., 2001), accounting returns (Wei and Zhang, 2006), and sales and employment growth (Comin and Mulani, 2006), by demonstrating an underlying rise in firm-specific TFP growth volatility. We consider a range of explanations for increasingly firm-specific TFP growth volatility – heterogeneous abilities to exploit new technologies (Schumpeter, 1912), financial development letting smaller and more volatile firms list (Pastor and Veronesi, 2003; Fama and French 2004), and intensified domestic or international competition making markets less forgiving of slip-ups (Philippon, 2003; Irvine and Pontiff, 2005; Gaspar and Massa, 2006). Multiple regressions on proxies for these effects highlight a uniquely and consistently significant pattern of industries with intensified IT use also exhibiting elevated firm-specific TFP growth volatility.

Our results are thus consistent with theoretical and empirical work positing that IT is a GPT inducing a wave of creative destruction across large swathes of the U.S. economy in the late 20th century (Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998; Jovanovic and Rousseau, 2005; Chun *et al.*, 2008; and others), and augment these insights by suggesting elevated firm-specific output and TFP growth volatilities are operational ways of tracking this wave. Creative destruction has extreme winners and losers, and their unfolding fates elevate firm-specific TFP growth volatility, and thence output growth volatility. Our findings thus also validate models that formalize Schumpeter's (1912) process of creative destruction, such as Aghion and Howitt (1992).

Our findings also help illuminate the Great Moderation, the secular downward trend in U.S. GDP volatility (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001). This attenuation may well have multiple causes. For example, shocks to industries may attenuate or grow less correlated and thus more prone to cancel out (Comin and Philippon, 2005; Irvine and Schuh, 2005, 2007). Our findings take these arguments a step further, showing firm-level shocks to be decreasingly correlated within each industry, even as their magnitudes rise. This makes firm-level shocks more prone to cancel out in the aggregate, permitting an attenuation of aggregate shocks.

Finally, Davis *et al*. (2006) report declining employment growth volatility among unlisted firms which account for over two thirds of private sector employment, and argue that decreasing volatility among these firms more than compensates for rising volatility among listed firms. This useful contribution cannot be the end of the story, though, because the volatility of the growth rate of the aggregated output of all firms in Compustat also falls, even as their firm-level output growth volatilities rise. Moreover, listed firms are of interest *per se* because they account for about half of U.S. aggregate value-added and 95% of private sector R&D spending (Comin and Mulani, 2007). Although, further comparison of listed versus unlisted firms remains a promising research avenue, the qualitative change we detect in economic shocks to listed firms is likely a substantial contributor to the Great Moderation.

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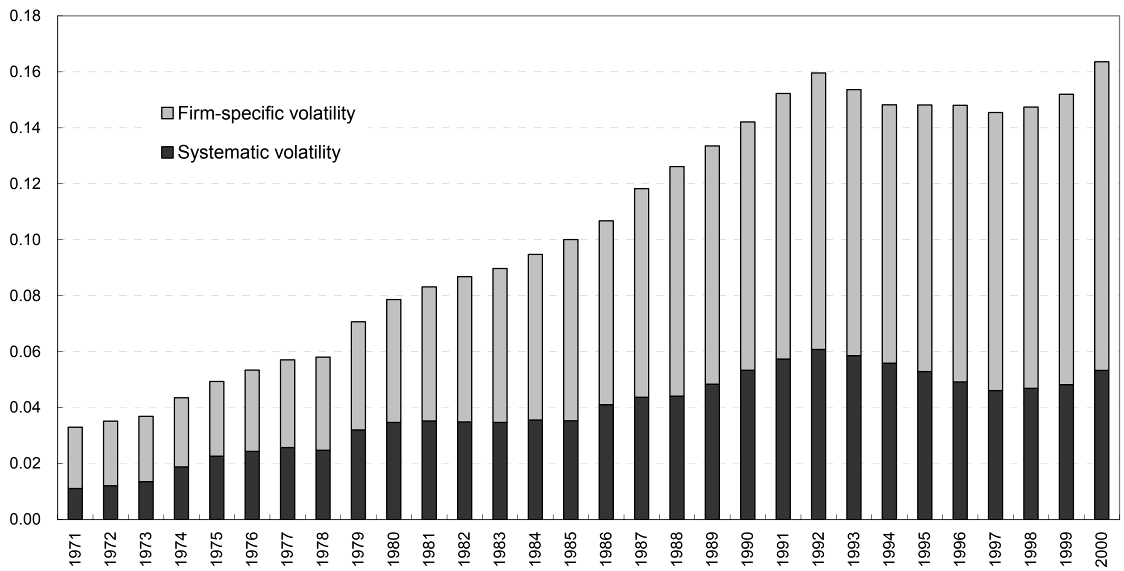
Figure 1. Firm-Level and Economy-Level Output Growth Volatilities

In Panel A, firm-level output (real value-added) growth volatility (time series variation through overlapping ten-year rolling windows ending in the designated years) is decomposed into systematic (industry- or economy-related) and firm-specific components. Systematic volatility is normalized explained variation obtained from firm-level regressions of output growth rate on industry and economy average growth rates using ten-year rolling windows. Industry and economy average growth rates exclude the firm in question to avoid spurious correlation problem where one firm is a substantial part of the economy or an industry. Firm-specific volatility is normalized unexplained variation in these same regressions. In estimating volatility measures, firms with fewer than 5 annual observations in each ten-year window are dropped. Data graphed are economy averages, weighting industry estimates by prior year's industry value-added. In Panel B, aggregate output growth rate is the value-added-weighted sum of real value-added growth rates of all firms used in Panel A. Aggregate output growth volatility is time series standard deviation in aggregate output growth rates in successive ten-year windows ending in the designated years. Our sample is composed of all firms in Compustat excluding the finance sector (SIC 6000 to 6999).

Panel A. Firm-Level Output Growth Volatility Decomposed



Panel B. Sample Aggregate Output Growth Volatility

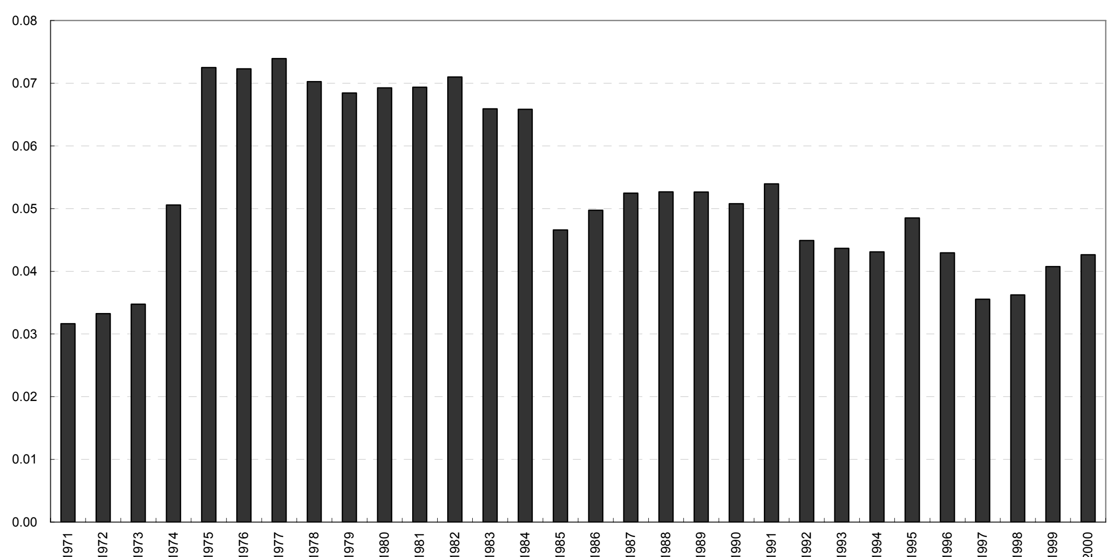
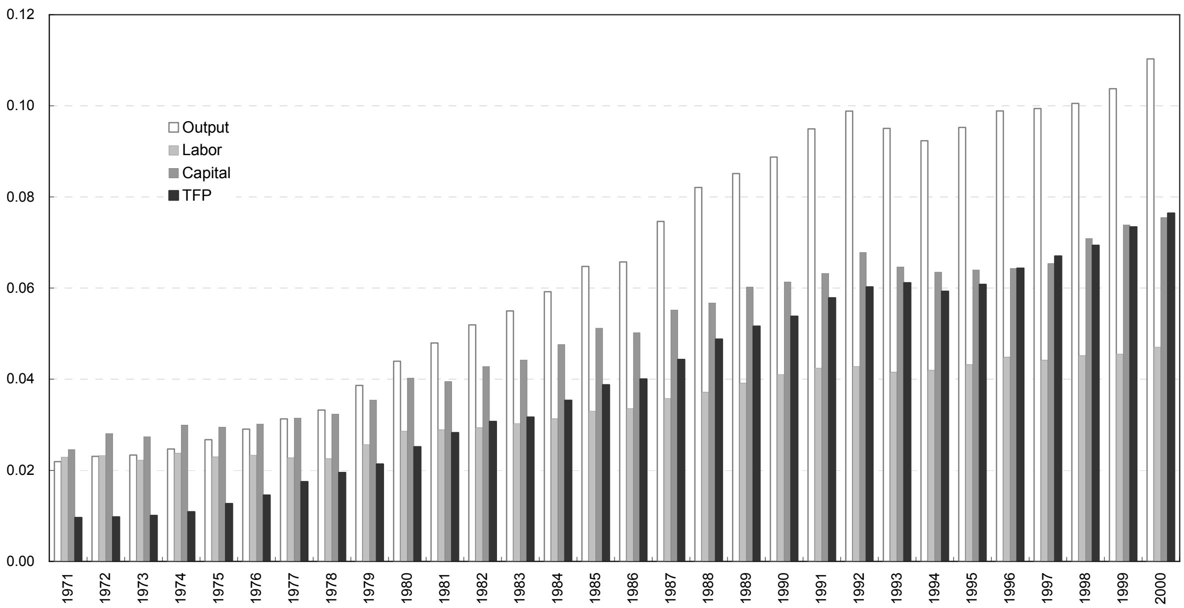


Figure 2. Firm-Specific Volatility of Output, Input, and TFP Growth

Firm-specific volatility is normalized unexplained variation obtained from firm-level regressions of output, labor, capital, and total factor productivity (TFP) growth rates on industry and economy average growth rates of those variables using ten-year rolling windows. Our sample is composed of all firms in Compustat in the manufacturing and non-manufacturing (approximately two-digit) industries excluding the finance sector (SIC 6000 to 6999). The sample excludes industries with fewer than 5 firms. Data graphed are economy averages, weighting industry estimates by prior year's industry value-added. Panel B plots ratios of firm-specific TFP growth volatility over firm-specific input growth volatility.

Panel A. Firm-Specific Volatility



Panel B. Ratio of Firm-Specific TFP over Input Growth Volatility

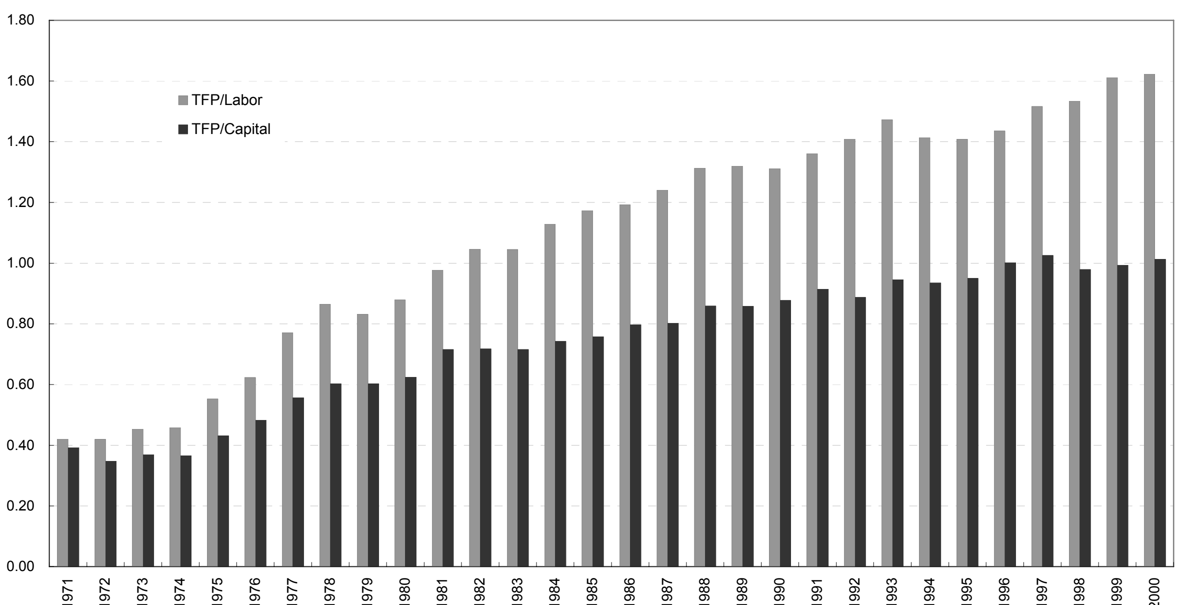


Figure 3. Expansion in Industry Firm-Specific Volatility

Twenty-year long-differences in firm-specific volatility measures are defined as logarithms of averages across the 1990s (1991-2000) less logarithms of averages across the 1970s (1971-1980). This figure reports annualized expansion rates for each industry, long-differences divided by 20 years, as percentage. The sample of 41 industries excludes finance industries (SIC 6000 to 6999) and industries with fewer than 5 firms. * denotes 15 largest industries based on industry value-added averaged over the 1970s. Data are sorted by expansion rate of firm-specific output growth volatility.

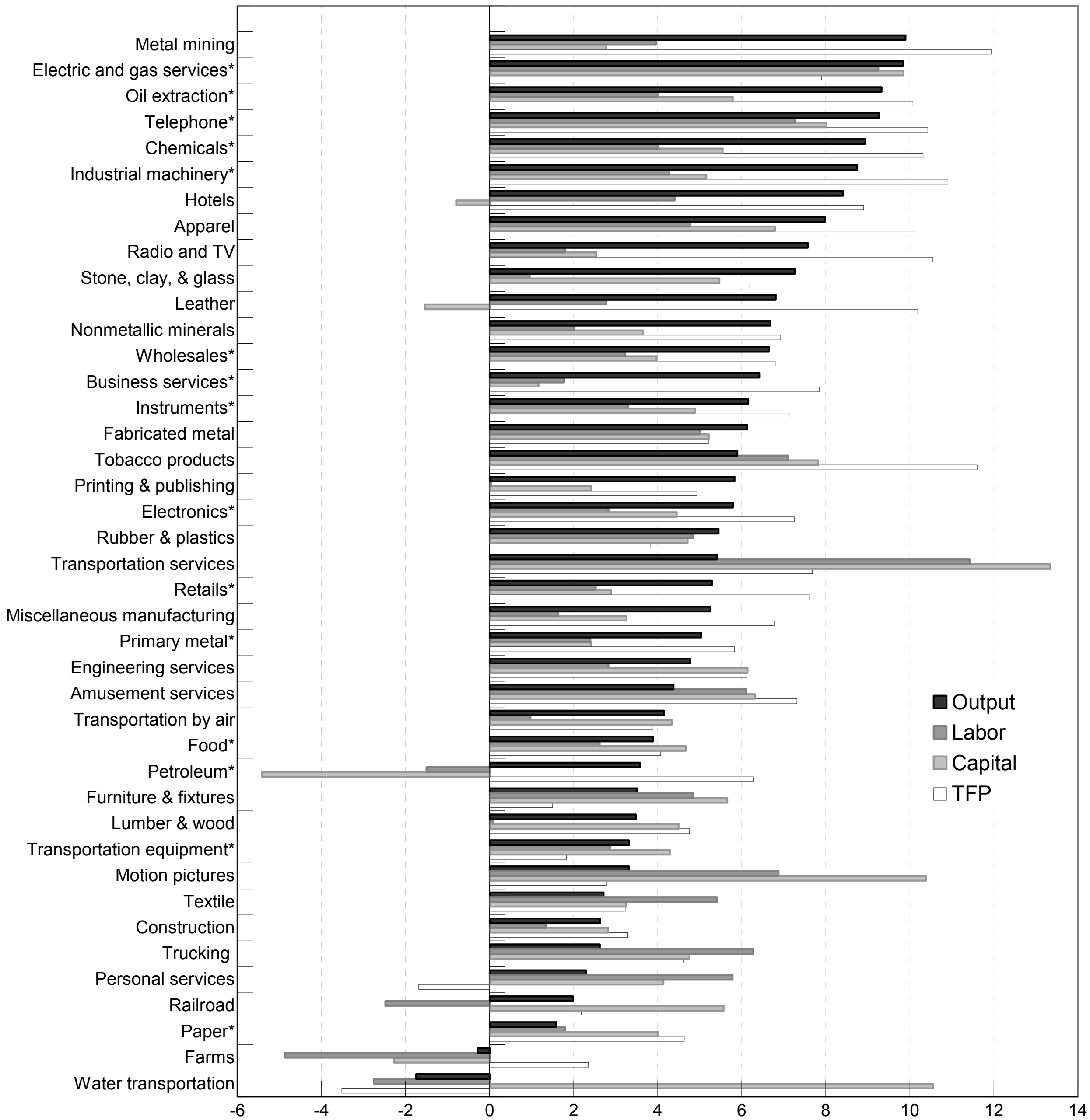


Figure 4. Correlation Coefficients of Firm-Level Output, Input, and TFP Growth

Correlation coefficients are the averages of pairwise correlations among 500 firms randomly chosen in each ten-year rolling window from the full sample. Our full sample is composed of all firms in Compustat in the manufacturing and non-manufacturing industries excluding the finance sector (SIC 6000 to 6999). The sample excludes firms with fewer than 5 observations in each ten-year window.

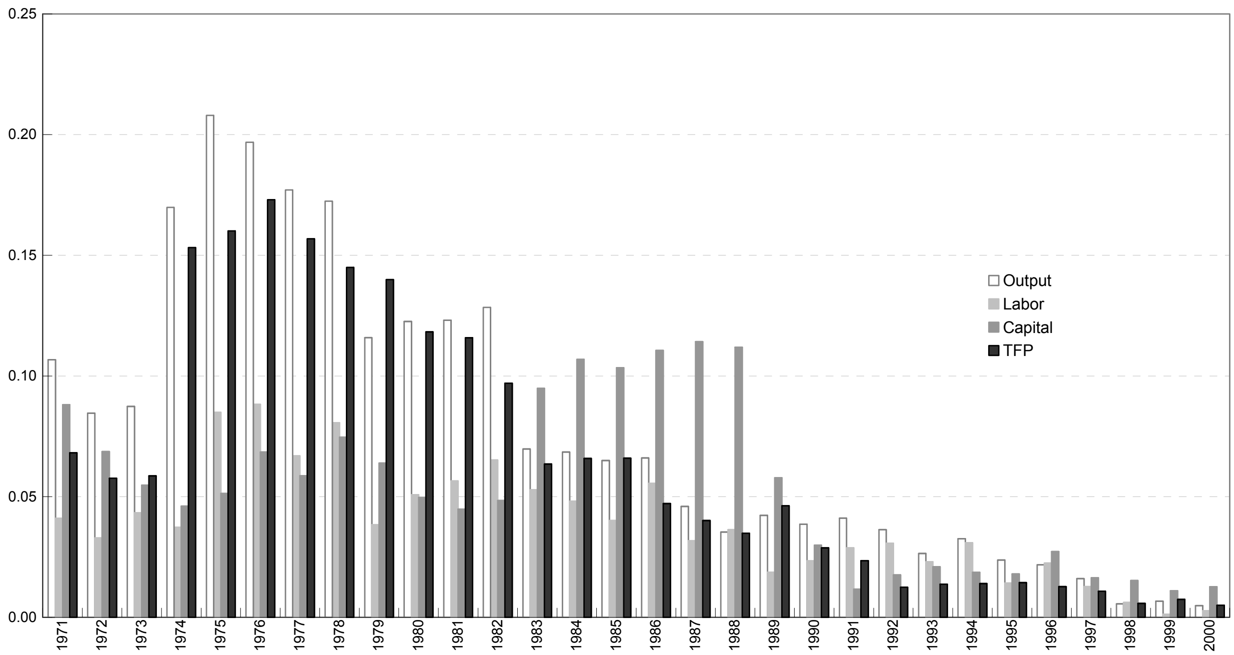
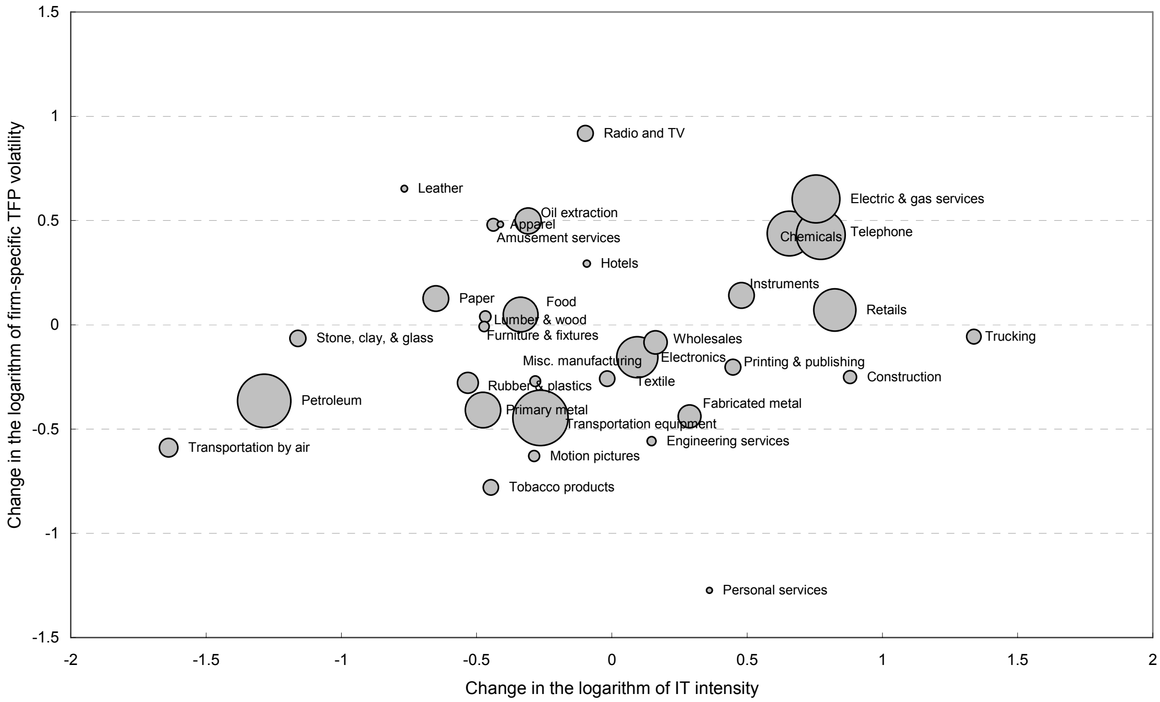


Figure 5. Increases in Firm-Specific TFP Growth Volatility and IT Intensity

The figure plots industry-by-industry changes in the logarithm of firm-specific TFP growth volatility from the 1970s (1971-1980) to 1990s (1991-2000) against the changes in the logarithm of information technology (IT) intensity in the same period. The size of each bubble indicates industry's value-added averaged across the 1970s.

Panel A. Firm-Specific TFP Growth Volatility



Panel B. Relative Firm-Specific TFP Growth Volatility

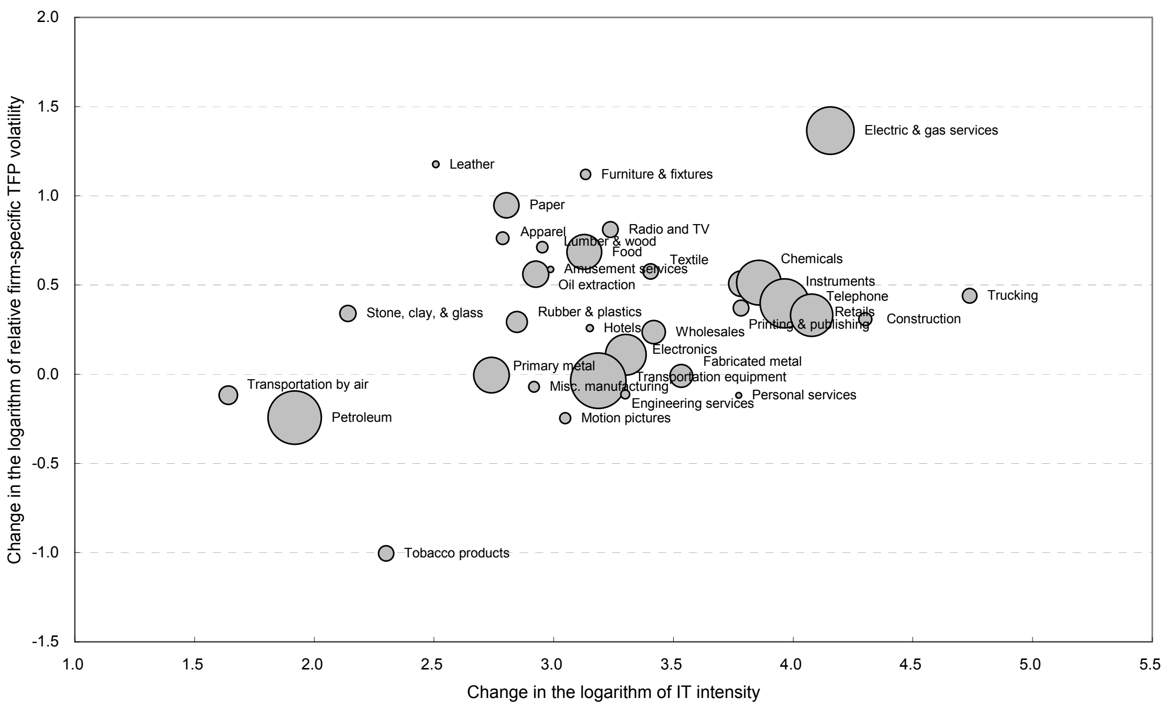


Table 1. Annualized Firm-Specific Volatility Expansion Rates: Summary Statistics

Firm-level output (real value-added), labor (the number of employees), capital, and total factor productivity (TFP) growth rate volatilities (time series variation through ten-year rolling windows ending in the designated years) are decomposed into systematic (industry- or economy-related) and firm-specific components. Systematic volatility is normalized explained variation obtained from firm-level regressions of output, labor, capital, and TFP growth rates on industry and economy average growth rates of those variables using ten-year rolling windows. Industry and economy average growth rates exclude the firm in question to avoid spurious correlation problem where one firm is a substantial part of the economy or an industry. Firm-specific volatility is normalized unexplained variation in these same regressions. Relative firm-specific volatility is the ratio of firm-specific volatility to systematic volatility. In estimating volatility measures, firms with fewer than 5 annual observations in each ten-year window are dropped. Volatility expansion rates are defined as logarithms of averages across the 1990s (1991-2000) less logarithms of averages across the 1970s (1971-1980) and are annualized and expressed as percentage. Volatility measures are weighted by industry value-added averaged across the 1970s. Our sample is composed of all firms in Compustat except the finance sector (SIC 6000 to 6999) and industries with fewer than 5 firms.

Panel A. Annualized Expansion Rates in Firm-Specific Volatility (all numbers in percentage)

		Mean	Median	Standard deviation	Min.	Max.	Skewness
Firm-Specific Volatility							
Output	$g\left(\sigma^2_{\varepsilon,i}(Y)\right)$	6.045	5.789	2.578	-1.744	9.901	0.108
Labor	$g\left(\sigma^2_{\varepsilon,i}(L)\right)$	3.418	2.862	2.955	-4.868	11.427	0.201
Capital	$g\left(\sigma^2_{\varepsilon,i}(K)\right)$	4.106	4.453	3.899	-5.414	13.343	-1.137
TFP	$g\left(\sigma^2_{\varepsilon,i}(TFP)\right)$	6.831	7.251	2.948	-3.515	11.936	-0.289
Relative Firm-Specific Volatility							
Output	$g\left(\psi_i(Y)\right)$	1.486	1.363	2.503	-8.457	7.454	-0.779
Labor	$g\left(\psi_i(L)\right)$	0.508	0.384	1.574	-5.044	5.252	-0.125
Capital	$g\left(\psi_i(K)\right)$	1.178	0.761	1.833	-3.837	7.362	1.178
TFP	$g\left(\psi_i(TFP)\right)$	1.605	1.653	2.324	-5.025	8.861	0.708

Panel B. Annualized Expansion Rates in Firm-Specific TFP Relative to Input Growth Volatility

	Mean	Median	Standard deviation	Min.	Max.	Skewness
Firm-Specific Volatility						
$g\left(\sigma^2_{\varepsilon,i}(TFP)\right)-g\left(\sigma^2_{\varepsilon,i}(L)\right)$	3.413	3.855	3.218	-7.463	8.749	-0.415
$g\left(\sigma^2_{\varepsilon,i}(TFP)\right)-g\left(\sigma^2_{\varepsilon,i}(K)\right)$	2.725	2.799	4.322	-14.065	11.729	0.487
Relative Firm-Specific Volatility						
$g\left(\psi_i(TFP)\right)-g\left(\psi_i(L)\right)$	1.097	0.568	2.960	-8.867	12.435	0.782
$g\left(\psi_i(TFP)\right)-g\left(\psi_i(K)\right)$	0.427	0.548	2.174	-6.430	8.459	-0.226

Table 2. Annualized Firm-Specific Volatility Expansion Rates: Correlations

Firm-level output, labor, capital, and TFP growth rate volatilities (time series variation through ten-year rolling windows ending in the designated years) are decomposed into systematic (industry- or economy-related) and firm-specific components. Systematic volatility is normalized explained variation obtained from firm-level regressions of output, labor, capital, and TFP growth rates on industry and economy average growth rates of those variables using ten-year rolling windows. Industry and economy average growth rates exclude the firm in question to avoid spurious correlation problem where one firm is a substantial part of the economy or an industry. Firm-specific volatility is normalized unexplained variation in these same regressions. Relative firm-specific volatility is the ratio of firm-specific volatility to systematic volatility. In estimating volatility measures, firms with fewer than 5 annual observations in each ten-year window are dropped. Volatility expansion rates are defined as logarithms of averages across the 1990s (1991-2000) less logarithms of averages across the 1970s (1971-1980) and are annualized and expressed as percentage. Volatility measures are weighted by industry value-added averaged across the 1970s. Our sample is composed of all firms in Compustat except the finance sector (SIC 6000 to 6999) and industries with fewer than 5 firms. Numbers in parentheses are probability levels at which the null hypothesis of a zero coefficient can be rejected. Coefficients significant at 10% or better are in boldface.

	Firm-Specific Volatility				***Relative Firm-Specific Volatility***		
	Output	*Labor*	*Capital*		*Output*	*Labor*	*Capital*
Labor	**0.717**			*Labor*	0.001		
	(0.000)				(0.996)		
Capital	**0.570**	**0.844**		*Capital*	**0.533**	-0.198	
	(0.000)	(0.000)			(0.000)	(0.216)	
TFP	**0.832**	**0.406**	0.227	*TFP*	**0.756**	-0.121	**0.474**
	(0.000)	(0.009)	(0.154)		(0.000)	(0.452)	(0.002)

Table 3. Industry-Level Explanatory Variables: Summary Statistics

All variables beginning with Δ denote long-differences, defined as logarithms of averages across the 1990s (1991-2000) less logarithms of averages across the 1970s (1971-1980). IT intensity, *IT*, is the ratio of information technology capital (computers and software) to other capital. *R&D* is capitalized past research and development spending over property, plant and equipment (PP&E). *Age* is the average years the industry's firms have been listed in CRSP; *Size* is the average sales of firms; *H* is a sales-based Herfindahl index; and *M* is the industry's imports over gross output. The indicator variable δ_{dereg} is one for deregulated industries and zero otherwise; and δ_{nmfg} is one for non-manufacturing industries and zero otherwise. Observations are weighted by industry value-added averaged across the 1970s.

			Mean	Median	Standard deviation	Min.	Max.	Skewness
	Technological Progress							
1.	*Information technology intensity*	*Δln(IT)*	3.287	3.301	0.752	1.642	4.738	-0.466
2.	*R&D intensity*	*Δln(R&D)*	-0.012	0.133	0.913	-2.549	2.203	-1.145
	Corporate Demography							
3.	*Industry mean firm age*	*Δln(Age)*	0.167	0.157	0.180	-0.435	0.701	-0.491
4.	*Industry mean firm size*	*Δln(Size)*	0.493	0.547	0.429	-0.692	1.413	-0.266
	Domestic Competition							
5.	*Industry Herfindahl index*	*ΔH*	-0.026	-0.010	0.069	-0.217	0.199	-1.504
6.	*Deregulated industry dummy*	δ_{dereg}	0.210	0.000	0.412	0.000	1.000	1.426
	Global Competition							
7.	*Imports as fraction of industry sales*	*ΔM*	0.092	0.006	0.151	-0.011	1.625	3.259
8.	*Non-manufacturing industry dummy*	δ_{nmfg}	0.377	0.000	0.491	0.000	1.000	0.510

Table 4. Industry-Level Explanatory Variables: Correlations

All variables beginning with Δ denote long-differences, defined as logarithms of averages across the 1990s (1991-2000) less logarithms of averages across the 1970s (1971-1980). IT intensity, *IT*, is the ratio of information technology capital (computers and software) to other capital. *R&D* is capitalized past research and development spending over property, plant and equipment (PP&E). *Age* is the average years the industry's firms have been listed in CRSP; *Size* is the average sales of firms; *H* is a sales-based Herfindahl index; and *M* is the industry's imports over gross output. The indicator variable δ_{dereg} is one for deregulated industries and zero otherwise; and δ_{nmfg} is one for non-manufacturing industries and zero otherwise. Observations are weighted by industry value-added averaged across the 1970s. Numbers in parentheses are probability levels at which the null hypothesis of a zero coefficient can be rejected. Coefficients significant at 10% or better are in boldface.

		1	*2*	*3*	*4*	*5*	*6*	*7*
1.	*Δln(IT)*							
2.	*Δln(R&D)*	-0.196 (0.259)						
3.	*Δln(Age)*	-0.262 (0.112)	-0.042 (0.804)					
4.	*Δln(Size)*	-0.256 (0.121)	-0.052 (0.759)	0.006 (0.971)				
5.	*ΔH*	-0.221 (0.183)	-0.195 (0.242)	**0.421** (0.006)	0.234 (0.141)			
6.	δ_{dereg}	**0.459** (0.004)	0.131 (0.434)	-0.208 (0.193)	0.023 (0.888)	**-0.334** (0.033)		
7.	*ΔM*	-0.180 (0.280)	0.167 (0.317)	0.037 (0.820)	0.255 (0.108)	0.142 (0.374)	**-0.316** (0.044)	
8.	δ_{nmfg}	**0.587** (0.000)	**-0.355** (0.029)	**-0.268** (0.090)	-0.089 (0.580)	**-0.380** (0.014)	**0.663** (0.000)	**-0.477** (0.002)

Table 5. Regressions Explaining Expanding Firm-Specific TFP Growth Volatility

Regressions are weighted least squares (WLS) with observations weighted by industry value-added averaged across the 1970s (1971-1980). In Panel A, the dependent variable is the long-difference in firm-specific TFP growth volatility, defined as that variable's logarithm of average across the 1990s (1991-2000) less the same quantity across the 1970s (1971-1980), $\Delta\ln\left[\sigma^2_{\varepsilon,i}(TFP)\right]$. Explanatory variables are defined as in Table 3. The additional control variable $\Delta\ln\left[\sigma^2_{s,i}(TFP)\right]$ is the long-difference in the logarithm of average systematic TFP growth volatility across the 1990s less the same quantity across the 1970s. In Panel B, the dependent variable is the long-difference in relative firm-specific TFP growth volatility, defined as that variable's logarithm of average across the 1990s less the same quantity across the 1970s, $\Delta\ln\left[\psi_i(TFP)\right] \equiv \Delta\ln\left[\sigma^2_{\varepsilon,i}(TFP)\right] - \Delta\ln\left[\sigma^2_{s,i}(TFP)\right]$. The sample excludes IT-producing and finance (SIC 6000 to 6999) industries, and industries for which explanatory variables are unavailable. Numbers in parentheses are probability levels, based on *t*-statistics adjusted for heteroskedasticity, at which the null hypothesis of a zero coefficient can be rejected. Coefficients significant at 10% or better are in boldface.

Panel A. Expansion of Firm-Specific TFP Growth Volatility

	5a.1	*5a.2*	*5a.3*	*5a.4*	*5a.5*	*5a.6*	*5a.7*	*5a.8*	*5a.9*	*5a.10*
Technological Progress										
Δln(*IT*)	**0.354**					**0.357**	**0.322**	**0.275**	**0.240**	**0.213**
	(0.000)					(0.000)	(0.001)	(0.004)	(0.001)	(0.020)
Δln(*R&D*)		-0.023				0.017	0.008	-0.022	-0.038	0.011
		(0.748)				(0.763)	(0.887)	(0.713)	(0.395)	(0.874)
Corporate Demography										
Δln(*Age*)			-0.388				-0.013		0.253	0.276
			(0.484)				(0.978)		(0.531)	(0.492)
Δln(*Size*)			**-0.349**				**-0.257**		**-0.283**	**-0.293**
			(0.019)				(0.031)		(0.046)	(0.054)
Domestic Competition										
Δ*H*				-0.963				-1.041	-1.305	-1.171
				(0.391)				(0.330)	(0.134)	(0.185)
δ_{dereg}				**0.433**				0.222	**0.254**	0.101
				(0.072)				(0.303)	(0.080)	(0.638)
Global Competition										
Δ*M*					0.142					0.038
					(0.669)					(0.921)
δ_{nmfg}					**0.480**					0.211
					(0.011)					(0.355)
Systematic Volatility and Intercept										
$\Delta\ln\left[\sigma^2_s(TFP)\right]$	**0.703**	**0.642**	**0.545**	**0.623**	**0.615**	**0.698**	**0.652**	**0.680**	**0.647**	**0.616**
	(0.000)	(0.001)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	-0.457	**0.761**	**1.098**	**0.663**	**0.599**	-0.462	-0.186	-0.251	-0.032	0.044
	(0.152)	(0.001)	(0.000)	(0.001)	(0.000)	(0.145)	(0.685)	(0.456)	(0.933)	(0.912)
Adjusted R^2	0.671	0.449	0.529	0.591	0.606	0.661	0.673	0.690	0.721	0.707
Sample size	33	33	33	33	33	33	33	33	33	33

[Table 5 Continued]

Panel B. Expansion of Relative Firm-Specific TFP Growth Volatility

	5b.1	*5b.2*	*5b.3*	*5b.4*	*5b.5*	*5b.6*	*5b.7*	*5b.8*	*5b.9*	*5b.10*
Technological Progress										
$\Delta\ln(IT)$	**0.390**					**0.378**	**0.409**	**0.283**	**0.299**	**0.310**
	(0.003)					(0.002)	(0.000)	(0.001)	(0.000)	(0.002)
$\Delta\ln(R\&D)$		-0.103				-0.052	-0.045	-0.072	-0.089	-0.118
		(0.319)				(0.615)	(0.516)	(0.461)	(0.184)	(0.113)
Corporate Demography										
$\Delta\ln(Age)$			0.489				0.840		**0.884**	**0.850**
			(0.490)				(0.127)		(0.049)	(0.059)
$\Delta\ln(Size)$			-0.250				-0.135		-0.187	-0.190
			(0.109)				(0.267)		(0.146)	(0.219)
Domestic Competition										
ΔH				1.601				1.240	-0.145	-0.216
				(0.345)				(0.410)	(0.904)	(0.854)
δ_{dereg}				**0.662**				0.440	**0.388**	**0.486**
				(0.059)				(0.117)	(0.037)	(0.039)
Global Competition										
ΔM					0.149					0.001
					(0.783)					(0.999)
δ_{nmfg}					0.450					-0.129
					(0.115)					(0.560)
Intercept	**-0.953**	**0.327**	**0.361**	**0.225**	0.155	**-0.916**	**-1.102**	**-0.669**	**-0.810**	**-0.817**
	(0.010)	(0.017)	(0.001)	(0.031)	(0.364)	(0.006)	(0.006)	(0.009)	(0.007)	(0.010)
Adjusted R^2	0.351	0.012	0.014	0.224	0.146	0.340	0.412	0.405	0.478	0.441
Sample size	33	33	33	33	33	33	33	33	33	33

Table 6. Firm-Specific TFP Growth Volatility, Firm Turnover Rate, and Firm-Specific Stock Return Volatility

The dependent variable in columns 6.1 and 6.2 is the long-difference in industry turnover rate. Industry turnover rate is defined as the probability of a firm dropping out of the industry's top sales quintile within five years, as in Comin and Philippon (2005). The long-difference of the variable is the logistically transformed average probability across the 1990s (1991-2000) less the same quantity across the 1970s (1971-1980). The dependent variable in columns 6.3 and 6.4 is the corresponding long-difference in relative firm-specific stock return volatility. Right-hand side variables are long-differences in firm-specific, systematic, and relative firm-specific TFP growth volatilities. Observations are weighted by each industry's value-added averaged across the 1970s. The sample excludes finance industries (SIC 6000 to 6999), and industries with fewer than 5 firms. Numbers in parentheses are probability levels, based on *t*-statistics adjusted for heteroskedasticity, at which the null hypothesis of a zero coefficient can be rejected. Coefficients significant at 10% or better are in boldface.

	Turnover Rate		*Relative Firm-Specific Stock Return Volatility*	
	6.1	*6.2*	*6.3*	*6.4*
TFP Volatility				
Firm-specific	**0.122**		**0.191**	
	(0.007)		(0.051)	
Systematic	**-0.107**		**-0.249**	
	(0.052)		(0.009)	
Relative Firm-specific		**0.109**		**0.236**
		(0.011)		(0.010)
Intercept	**0.121**	**0.153**	**0.552**	**0.504**
	(0.004)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.159	0.172	0.302	0.299
Sample size	41	41	41	41

Appendix

Figure A. Aggregate TFP Growth Volatility: Compustat versus BLS

Compustat TFP growth rate estimates are based on data for listed firms in all non-financial industries, while BLS data are for the entire private sector. BLS TFP growth rates are from *Multifactor Productivity Trends, 2001*. Volatilities are standard deviations of TFP growth rates estimated using ten-year rolling windows.