Working Papers

FEDERAL RESERVE BANK OF BOSTON™

No. 14-15

Vanishing Procyclicality of Productivity? Industry Evidence

J. Christina Wang

Abstract:

Labor productivity (LP) in the United States has gone from being procyclical to acyclical since the mid-1980s. Using industry-level data, this paper first shows that total factor productivity (TFP), which is LP net of capital deepening, has also become much less correlated with output as well as inputs over the same period. Moreover, the bulk of the decline in aggregate TFP's cyclicality is attributable to service industries. This paper then uses the industry data to investigate the reasons for the change in the cyclicality of productivity. By decomposing TFP into technical change and input utilization, it finds that TFP's correlation with inputs has fallen and that the main reason for this decline is that technology shocks, which remain negatively correlated with inputs (that is, contractionary) in the short run, have come to account for a larger share of the fluctuations in TFP. Evidence suggests that this change is the result of more flexible labor markets together with more persistent technology shocks since the mid-1980s, causing firms to do less adjustment along the intensive margin. By comparison, the evidence does not appear to support the competing hypothesis that the reduction in the productivity-input correlation could be due to increasing investment in intangible capital.

Keywords: productivity, technology, business cycle, utilization, aggregation, labor hoarding

JEL Classifications: D24, E22, E24, E32.

J. Christina Wang is a senior economist and policy advisor in the research department of the Federal Reserve Bank of Boston. E-mail address: christina.wang@bos.frb.org.

I would like to thank Susanto Basu, John Fernald, Giovanni Olivei, and Joe Peek for helpful discussions and comments, and Valerie Ramey for a very thoughtful discussion at the 2014 NBER/CRIW summer session. A great many thanks to Alison Pearson and Vladimir Yankov for excellent research assistance, and to Mike Corbett for help with the union membership data. Special thanks to Dale Jorgenson and coauthors for making their industry data available, and to Chris Kask of the Bureau of Labor Statistics for his assistance with the BLS manufacturing data.

This version: December 31, 2014

I. Introduction

During the last recession, U.S. labor productivity (LP) took a sharp but brief dive for three quarters around the height of the financial crisis in 2008:Q4 and then recovered to a brisk pace of over 3 percent per annum on average over the first six quarters of the recovery. The robust performance of productivity early in the recovery contrasts markedly with the sluggish growth of output, and even more with the lack of recovery in employment. This pattern has renewed interest in understanding why productivity has become much less procyclical in recent decades. This is an important topic because the cyclicality of productivity has implications for how we model business cycles. In particular, it is important to know whether technology shocks are the driving force of cycles and to understand how they are propagated. Understanding the cyclicality of productivity is also important for monetary policy because it affects the trend-cycle decomposition and in turn the projection of trend GDP growth as well as the assessment of the economy's output gap.

A number of papers have investigated the aggregate time-series data and proposed mechanisms that may explain the observed changes. These papers rely entirely on dynamic stochastic general equilibrium (DSGE) models for identification: different structural models imply different relationships among economic variables in terms of volatility and comovement. This study instead uses the cross-industry dimension as an alternative and complementary method for identifying the mechanisms that have led to productivity's diminished procyclicality. Industries differ along many dimensions that matter, such as labor market institutions, sensitivity to monetary policy, and the ways these attributes change over time. These differences imply that each proposed mechanism should have different degrees of relevance across industries. Hence, cross-industry differences in the change of the cyclical properties of productivity should shed light on which proposed mechanisms are responsible for the change, and on their relative importance.

Moreover, disaggregated data are better suited than aggregates to account for the contribution of unmeasured input utilization to productivity growth and to uncover the responses of the economy to changes that are truly related to technology per se. We will then be able to examine not only the unconditional correlation of output and inputs with LP, but also their response to technology shocks specifically. To this end, we extend the analysis beyond LP to total factor productivity (TFP). It is by now well understood that measured TFP growth generally does not equal changes in true technology alone. Instead, as explained in detail later, it also includes unmeasured changes in the intensity with which inputs are used. Applying a method developed in previous studies, we correct measured TFP for the unmeasured utilization of inputs to evaluate the relative contribution of technology versus utilization to the change in the cyclical dynamics of TFP. To a first order, utilization is shown to be proportional to average hours per worker, with a scaling parameter that varies by firm or industry. Aggregate utilization is thus the weighted sum of rescaled hours per worker in each industry. The identification assumptions used to derive this utilization proxy are little more than cost-minimization by firms. These assumptions are satisfied in almost all DSGE models, so the results in this paper are relevant to a large class of models. This contrasts with the much more stringent condition required of the DSGE approach, where the validity of the results depends on the complete general-equilibrium structure of the specific model.

We discover four sets of "stylized facts." First, for the overall nonfarm business sector, although the procyclicality of measured TFP has fallen substantially, the cyclicality of technology has changed little. Specifically, technology shocks remain about equally volatile over time, whereas input utilization becomes less volatile after the mid-1980s. Since utilization is adjusted in response to both technology and demand shocks, this suggests that demand shocks are on average smaller after the mid-1980s. The greater relative volatility of the technology term means it accounts for a larger fraction of TFP's correlations with output and inputs after the mid-1980s. These correlations thus decline (that is, TFP becomes less procyclical) because the technology term is negatively correlated with inputs over all the sample years.

Second, we find that the extensive labor margin has become less responsive to technology shocks compared with the intensive margin since the mid-1980s. In fact, total nonfarm business employment responds less negatively to technology shocks after the mid-1980s, although neither the earlier negative response nor the change after 1984 is statistically significant. In contrast, average hours per worker, both in the aggregate and at the industry level, respond equally negatively in both subperiods.[1] This pattern can be explained by the finding that technology shocks likely have become more persistent since 1984. Anticipating additional productivity growth to follow an initial positive shock, firms today should choose to pare employment less and reduce the total input of hours more by cutting hours per worker, since the former is subject to adjustment cost, whereas the latter, as in most models, is not. Qualitatively, no reduction in hiring and firing costs is needed to effect this relative change in responsiveness of the intensive versus the extensive margin of labor input.

[1] This is consistent with the less negative response of utilization at the aggregate level since the mid-1980s because of changes in industry composition: decreases in shares of industries where utilization varies more for a given change in hours per worker, along with increases in shares of service industries, where utilization varies less with hours per worker.

Third, the unconditional volatility of hours per worker has likewise risen relative to that of employment since the mid-1980s, except in a handful of (mainly) service industries. (Note that this finding of the relative change does not depend on correct identification of the technology shocks.) On the other hand, the volatility of employment has risen relative to that of output. In fact, there is a robust relationship across industries between the decline in the cyclicality of TFP and the relative increase in the unconditional volatility of employment vis-à-vis value added. The finding that both margins of labor input have become more volatile relative to output suggests that both external and internal labor markets have experienced enhanced flexibility since the mid-1980s.

Last, with industry data, we can also examine whether the lower cyclicality of aggregate productivity results more from changes within each industry or from lower correlations across industries. We find that the major contributor is declines in within-industry cyclicality of productivity. This is perhaps not surprising, since the efficiency of input adjustments resulting from greater labor market flexibility likely improves more within individual industries than across industries. When we decompose aggregate TFP into technology, utilization, and resource-allocation terms, we find that the latter two combined can account for about a quarter, and no more than half, of the reduction in the procyclicality of TFP.

This paper is not the first to investigate the changing behavior of productivity. Gali and van Rens (2010) modeled the declining correlation between aggregate output and labor productivity as the result of lower costs of adjusting employment. This is because, in their model, firms can alter labor input through either the measured (extensive) margin of employment or the unmeasured (intensive) margin of effort; the former is subject to adjustment costs, whereas the latter is not. A lower adjustment cost leads firms to rely more on employment than on effort in adjusting labor input. The findings discussed above, however, do not support this explanation, since utilization has become more rather than less volatile relative to employment. Instead, changes in the persistence of shocks can explain the empirical fact, since the relative use of extensive versus intensive margins to adjust labor input also depends on the persistence of shocks, which is held constant in Gali and van Rens (2010).[2] We indeed find that the greater persistence of technology shocks helps to explain the changing response of employment relative to that of hours per worker after the mid-1980s, as described above.

[2] For example, Ramey and Vine (2006) show that less persistent demand shocks can explain the greater use of the intensive margin by car manufacturers since the mid-1980s.

It is also worth noting that in Gali and van Rens (2010), productivity always comoves positively with output and inputs in response to technology shocks, so they need preference shocks combined with decreasing returns to labor to obtain a negative productivity-input correlation on average. In contrast, this paper finds that technology shocks by themselves are enough to yield the negative correlation, since technology shocks remain contractionary over the sample period and account for a greater fraction of the variation in TFP after the mid-1980s, as reported above.

McGratten and Prescott (2007, 2012) proposed a different mechanism for the disappearing positive correlation between output and labor productivity, based on greater measurement error in the observed output. They argue that broadly defined research and development (R&D), which is poorly measured in general, has become ever more important over the past 30 years. The greater the unobserved R&D investment, the lower the correlation between observed output and productivity. We show that available industry data provide little support for this explanation, although better data are needed to gain a more accurate assessment because of the intrinsic difficulty of measuring intangible investment.

The remainder of this paper is organized as follows. Section 2 discusses mechanisms that can potentially lower the positive comovement between output and productivity. Section 3 presents confirming evidence on the decreased cyclicality of productivity measures for the overall private sector, based on aggregate series constructed using the industry data. Section 4 reports cross-industry patterns of the changing cyclicality of productivity and examines the contribution of greater labor market flexibility and possible intangible investment in the vanishing procyclicality of productivity. Section 5 concludes.

II. The Cyclical Relationship among Output, Labor Input and Productivity

This section discusses briefly the cyclical relationships among productivity, inputs, and output according to growth accounting, and the potential mechanisms that can cause the comovements among these variables to change. We focus on the realistic case where these variables are observed with error, paying special attention to the role of likely cyclical variations in measurement errors in the observed variables, since such errors can distort the measured cyclicality of productivity.

2.1 Cyclical Relationships with Systematic Measurement Errors

Since this study focuses on the correlation between TFP and inputs as the cyclicality measure of productivity, we first explain the relationship of this measure with the LP-output correlation, which is the cyclicality measure used in previous studies. We then show how the cyclicality of TFP can change even if the cyclicality of technical change stays the same over time, because of unmeasured variations in input use that cause TFP to deviate from true technical change. All the variables are measured in terms of growth rates, unless otherwise noted.

By definition, LP equals TFP plus capital deepening weighted by capital's share in value added:[3]

$$\mathrm{d}a = \mathrm{d}v - \mathrm{d}h = \left(\mathrm{d}v - \mathrm{d}x^V\right) + s_K^V\left(\mathrm{d}k - \mathrm{d}l\right) \equiv \mathrm{d}t + s_K^V\left(\mathrm{d}k - \mathrm{d}l\right), \tag{1}$$

where da, dv, dh, dl, dk, and dt are the growth rates of LP, value added (VA, the relevant output measure for the economy as a whole), total hours, labor services, capital services, and TFP, respectively.[4] dx^V is the growth rate of primary inputs, defined as $(s_K^V \mathrm{d}k + s_L^V \mathrm{d}l)$, where s_L^V and s_K^V are shares of labor and capital income in nominal VA, respectively. (dk – dl) measures capital deepening.

This implies the following relationship between the LP-VA correlation, the cyclicality measure used in previous studies, and the TFP-input correlation, the measure focused on in this study:[5]

$$\rho(\mathrm{d}a, \mathrm{d}v) = \rho(\mathrm{d}t, \mathrm{d}v)\frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}a)} + s_K^V \rho\left[\left(\mathrm{d}k - \mathrm{d}l\right), \mathrm{d}v\right]\frac{\sigma(\mathrm{d}k - \mathrm{d}l)}{\sigma(\mathrm{d}a)}, \text{ and} \tag{2}$$

$$\rho(\mathrm{d}t, \mathrm{d}v) = \rho(\mathrm{d}t, \mathrm{d}x^V)\frac{\sigma(\mathrm{d}x^V)}{\sigma(\mathrm{d}v)} + \frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)} \geq \rho(\mathrm{d}t, \mathrm{d}x^V). \tag{3}$$

where $\sigma(.)$ denotes a variable's volatility (that is, the square root of its variance) and $\rho(,)$ denotes correlation between variables. Equations (2) and (3) show that ρ(da, dv) can be expressed as the sum of ρ(dt, dx^V) and the cyclicality of capital deepening, each weighted by the related volatility ratio. This study focuses on ρ(dt, dx^V) because it is a cleaner measure of the cyclicality of true technical change. As will become clear, without unmeasured input variations or markup, TFP would equal true technical change.

Equations (2) and (3) make it clear that the changes in ρ(da, dv) and ρ(dt, dx^V) over time would most likely differ from each other unless the cyclicality of capital deepening and the volatility ratios all remained constant. We will show that empirically LP and TFP exhibit similar changes after 1984 in terms of their correlation with VA, both for the nonfarm business sector as a whole and at the industry level,

---

[3] In general, lower-case letters stand for the logarithm of the corresponding capital letters, and d stands for difference. Log differences measure growth rates. We omit the time subscripts for clarity. Also for clarity, we ignore labor quality—the difference between labor services and total hours (that is, dl – dh)—in all the derivations because its changes are much smaller than those of the other items, especially at a business cycle frequency.

[4] Note that TFP (growth) at the industry level is more commonly defined based on gross output, as will be defined in the next section and in Appendix I. VA-based TFP thus equals regular TFP divided by the VA share in gross output.

[5] See Appendix I for a detailed derivation of equation (3), which shows that TFP's correlation with VA always exceeds its correlation with primary inputs.

indicating that the volatility ratios in equation (2) and the cyclicality of capital deepening have remained fairly stable. On the other hand, the reduction in TFP's correlation with inputs exceeds that with output:

$$\Delta\rho(\mathrm{d}t,\mathrm{d}v)-\Delta\rho(\mathrm{d}t,\mathrm{d}x^{V})\approx\Delta\rho(\mathrm{d}t,\mathrm{d}x^{V})\left[\frac{\sigma_0(\mathrm{d}x^{V})}{\sigma_0(\mathrm{d}v)}-1\right]+\rho_0(\mathrm{d}t,\mathrm{d}x^{V})\Delta\left[\frac{\sigma(\mathrm{d}x^{V})}{\sigma(\mathrm{d}v)}\right]+\Delta\left[\frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)}\right]>0. \qquad (4)$$

The subscript 0 denotes the first (pre-1984) subperiod. As detailed in Appendix I, as long as TFP and inputs are positively correlated at the outset but become less so over time, TFP's correlation with inputs —the measure of cyclicality focused on in this study—must decline more than its correlation with output. In fact, TFP has become negatively correlated with inputs in the post-1984 period.

We now show that a change in the cyclicality of TFP does not necessarily mean the same change in the cyclicality of technology shocks, because of cyclical measurement errors in observed inputs. As Basu (1996), Basu and Fernald (2001), and Basu, Fernald, and Kimball (BFK, 2006) make clear, the standard TFP generally does not equal the true technical change, because it also contains the impact of unmeasured fluctuations in resource utilization (such as labor effort and capital utilization) and non-constant returns to scale or imperfect competition. In fact, these other influences can explain the bulk of the procyclicality of TFP and LP. Adjusting TFP for utilization enables us to analyze the relative contribution to the change in TFP's cyclicality of technical change versus utilization.

We adopt the method developed in Basu and Kimball (1997) to correct TFP (dt) and derive the true technology term (dz, also referred to as utilization-adjusted or purified TFP). As detailed in Appendix I, at a firm or industry level, TFP growth can be decomposed as follows:

$$\mathrm{d}t_{it}=\left(\mu_i-1\right)\mathrm{d}x_{it}^{V}+\mu_i\mathrm{d}u_{it}^{V}+\left(\mu_i-1\right)\frac{s_{Mi}}{1-s_{Mi}}\mathrm{d}m_{it}+\mathrm{d}z_{it}^{V}=\left(\mu_i-1\right)\frac{\mathrm{d}x_{it}}{1-s_{Mi}}+\mu_i\mathrm{d}u_{it}^{V}+\mathrm{d}z_{it}^{V}, \qquad (5)$$

where $\mathrm{d}x_{it}=s_{Li}\mathrm{d}l_{it}+s_{Ki}\mathrm{d}k_{it}+s_{Mi}\mathrm{d}m_{it}$ is the revenue-weighted growth of all inputs—labor (L), capital (K), and intermediate inputs (M)—weighted by their respective shares in revenue s_{Li}, s_{Ki}, and s_{Mi}. The factor shares sum to less than one if there is pure profit. The superscript "V" signifies that variables are measured on a VA basis. $\mathrm{d}x^{V}=\left(s_{Li}\mathrm{d}l+s_{Ki}\mathrm{d}k\right)/\left(1-s_{Mi}\right)$ is the growth rate of primary inputs. μ denotes the markup on gross output, which equals returns to scale with zero profit. The first term equals the contribution of observed inputs under non-constant returns to scale ($\mu_i \neq 1$). du^V denotes the composite labor and capital utilization term—unmeasured inputs. Only dz^V is the true technology shock.

TFP's correlation with inputs, dx^V, thus can be written (with *it* subscripts omitted for clarity) as:

$$\rho\left(\mathrm{d}t,\mathrm{d}x^{V}\right)=\frac{\mu_i-1}{1-s_{Mi}}\frac{\sigma(\mathrm{d}x)}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}x,\mathrm{d}x^{V}\right)+\mu_i\frac{\sigma(\mathrm{d}u^{V})}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}u^{V},\mathrm{d}x^{V}\right)+\frac{\sigma(\mathrm{d}z^{V})}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}z^{V},\mathrm{d}x^{V}\right). \qquad (6)$$

The first two correlations on the right-hand side (RHS) tend to be fairly positive because firms tend to adjust margins of input, observed or unobserved, in the same direction. This is why TFP can be quite positively correlated with inputs (that is, procyclical) without large positive, or even with negative, correlation between technology and inputs (the last term on the RHS), as found in BFK (2006). We will confirm later that technology and input remain negatively correlated throughout the sample years.

Since there is reasonable evidence for constant returns to scale (see, for example, Rotemberg and Woodford 1995), we set markup μ_i to 1 and derive the change in TFP-input correlation as follows:

$$\begin{aligned}\Delta\rho\left(\mathrm{d}t,\mathrm{d}x^V\right) &= \Delta\left[\frac{\sigma(\mathrm{d}u^V)}{\sigma(\mathrm{d}t)}\right]\rho_0\left(\mathrm{d}u^V,\mathrm{d}x^V\right)+\frac{\sigma_0(\mathrm{d}u^V)}{\sigma_0(\mathrm{d}t)}\Delta\rho\left(\mathrm{d}u^V,\mathrm{d}x^V\right)\\ &+\Delta\left[\frac{\sigma(\mathrm{d}z^V)}{\sigma(\mathrm{d}t)}\right]\rho_0\left(\mathrm{d}z^V,\mathrm{d}x^V\right)+\frac{\sigma_0(\mathrm{d}z^V)}{\sigma_0(\mathrm{d}t)}\Delta\rho\left(\mathrm{d}z^V,\mathrm{d}x^V\right).\end{aligned} \tag{7}$$

Obviously, the TFP-input correlation, $\rho(\mathrm{d}t, \mathrm{d}x^V)$, falls if either or both correlations on the RHS fall: $\Delta\rho(\mathrm{d}u^V, \mathrm{d}x^V) < 0$ or $\Delta\rho(\mathrm{d}z^V, \mathrm{d}x^V) < 0$, or both. But more importantly, equation (7) shows that, even if neither correlation on the RHS changed, $\rho(\mathrm{d}t, \mathrm{d}x^V)$ could still decline if relative volatilities changed to yield a negative first or third term on the RHS. The third term will be negative if technology shocks ($\mathrm{d}z^V$) become more volatile relative to TFP ($\mathrm{d}t$) because $\rho(\mathrm{d}z^V, \mathrm{d}x^V) < 0$, as discussed above. For the first term to be negative, utilization ($\mathrm{d}u^V$) needs to become less volatile relative to TFP because $\rho(\mathrm{d}u^V, \mathrm{d}x^V) > 0$ in general. Note that a smaller volatility of utilization, $\sigma(\mathrm{d}u^V)$, by itself will satisfy both of the above relative-volatility conditions and thus render both the first and the third terms negative, since $\mathrm{d}t$ is simply the sum of $\mathrm{d}z^V$ and $\mathrm{d}u^V$ when $\mu_i = 1$, and thus $\sigma^2(\mathrm{d}t) = \sigma^2(\mathrm{d}u^V) + \sigma^2(\mathrm{d}z^V) + 2\mathrm{cov}(\mathrm{d}u^V, \mathrm{d}z^V)$.

As we will show, the main reasons for the nonfarm business sector's TFP to exhibit diminished procyclicality after 1984 are: less volatile input utilization combined with equally volatile technical change to yield negative first and third terms in (7). A reduction in $\sigma(\mathrm{d}u^V)$ partly stems from less negative reaction of inputs to technology improvements, given that technology shocks have remained equally volatile throughout the sample years.[6] A lower $\sigma(\mathrm{d}u^V)$ likely also results from less volatile demand shocks after 1984. At the aggregate level, both a lower $\sigma(\mathrm{d}u^V)$ and a less negative $\mathrm{cov}(\mathrm{d}u^V, \mathrm{d}z^V)$ can also stem from changes in sectoral composition. We explore these potential channels later using industry data.

With this framework in mind, we now discuss the two primary mechanisms proposed to explain the decline, or even disappearance, of the procyclicality of LP in observed data since the mid-1980s.

[6] The effect of this change in lowering the TFP-input correlation is partly offset by the increase in $\mathrm{cov}(\mathrm{d}u^V, \mathrm{d}z^V)$, which has the partial effect of rendering the first term positive by raising $\sigma(\mathrm{d}t)$ relative to $\sigma(\mathrm{d}z^V)$.

2.2 Potential Mechanisms for the Diminished Procyclicality of Labor Productivity

We preface the discussion by noting that both proposed explanations rely on mismeasurement and its change over time. One proposal considers the impact of diminishing mismeasurement of inputs, while the other considers increasing mismeasurement of output.

2.2.1 Improvements in Labor Market Flexibility

Gali and van Rens (2010) propose that the main reason for the disappearance of the procyclicality of LP is that various reforms have made labor markets more flexible over time so that firms now face a lower cost to adjust employment—the extensive margin, which is subject to adjustment costs. All else being equal, firms would respond by adjusting labor input relatively more via employment and less via hours per worker or effort. In other words, there would be less labor hoarding.

Greater flexibility in the labor market is a change to the underlying structure of the economy, but it would not affect the measured cyclicality of productivity if we could precisely measure the true quantity of inputs. Some input elements, such as labor effort and capital utilization, are poorly measured, and the degree of mismeasurement most likely covaries positively with observed inputs. This tends to bias upward the observed cyclicality of productivity, but it also suggests a way to correct the mismeasurement—by using observed inputs as a proxy (as shown in Basu and Kimball 1997 and above). If structural changes cause the poorly measured elements of inputs, such as effort, to fluctuate less over the cycle, using observed inputs as a proxy should reduce this upward bias, all else being equal.[7]

Note, however, that the correlation between technology shocks and inputs, and in turn output, are always positive in a standard real business cycle (RBC) model. This is, in fact, the baseline case in Gali and van Rens (2010). To be consistent with the observed negative correlation between inputs and LP in data since the mid-1980s, Gali and van Rens (2010) have to introduce a preference shock that leads to a negative correlation between LP and inputs because of decreasing returns to scale of labor input.

In contrast, a baseline of negative correlations between technology shocks and inputs is consistent with findings in Gali (1999) and BFK (2006). Such a pattern can arise in a business cycle model with flexible prices but real frictions, as in Francis and Ramey (2005), or in a model with price rigidity or imperfect common knowledge, as discussed in BFK (2006). As we will show, industry data indicate that

[7] The implicit assumption here is that the total desired adjustment of labor input does not become so much more volatile that the absolute volatility of variation in effort rises even while its contribution relative to employment adjustment falls.

technology shocks remain negatively correlated with inputs over all sample years. This accounts for a greater share of TFP's correlation with inputs after 1984, leading to TFP's lower procyclicality.

2.2.2 Increased Importance of Intangible Investment

McGratten and Prescott (2007, 2012) propose an explanation for the diminished procyclicality of LP based on an increase in the share of private firms' activities devoted to creating intangible capital as compared with the share of operations devoted to producing market output. The impact of the greater importance of the unmeasured production of own capital on the cyclicality of productivity can be seen through derivations in Appendix II (equation (34)). In particular, it is shown that unmeasured output needs to start small relative to measured output in order for faster growth in the former to lead to falling procyclicality of LP. At the same time, the increase in such unmeasured productive activities, from a low base, would need to be sufficiently large to manifest in a discernable drop in the correlation between productivity and output.

McGratten and Prescott (2007, 2012) do not, however, address the timing of the increase in intangible investment, even though it would seem to be a central question. Why have firms boosted their engagement in activities that enhance future earnings power but do not generate current marketable output, starting sometime around the mid-1980s? Considering the timing, one reasonable candidate for the impetus to conduct a greater amount of broadly defined R&D activities is the growing importance of information and communications technology (ICT). Helpman and Trajtenberg (1998) argue that ICT is a new general-purpose technology (GPT) in that it can bring about structural changes to the production process of adopters. In order to take full advantage of the new GPT, however, firms that adopt ICT in their operations have to devote resources to reoptimize their production process. A number of studies (see, for example, Brynjolfsson and Hitt 2003, and Oliner et al. 2007; Brynjolfsson and Hitt 2000 offer an overview) have offered empirical evidence that, in order to effectively utilize the new capabilities of creating and sharing information enabled by ICT, adopting firms engage in reorganization or process restructuring, much of which is likely unmeasured and thus not counted as investment.

To the extent that there is a reasonably high degree of complementarity between investing in tangible ICT equipment and software, and spending on restructuring activities, the more a firm invests in the former, the more it should spend on the latter as well. The former experienced a boom in the late 1970s and early 1980s, when IBM personal computers became more capable yet more affordable. This would be consistent with the timing of the measureable decline in the cyclicality of productivity starting in the mid-1980s. The second boom in ICT investment took place in the second half of the 1990s, coinciding with a major cyclical boom, thus possibly biasing downward the observed cyclicality of LP.[8]

Since investment adds to the capital stock, intangible investment today leads to an opposite distortion in measured productivity later, in that the true capital stock and hence capital services are understated.[9] At the business cycle frequency, however, this intertemporal distortion is dominated by the bias caused by cyclical fluctuations in unobserved intangible investment, as shown in Basu et al. (BFOS 2004). To see the implication of this result for the observed cyclicality of TFP, we apply their equation (7), which derives TFP in the presence of intangible capital and investment, adapted below using notation consistent with that used in above derivations:[10]

$$\mathrm{d}y^{NT} - s_{K^{IT}}^{Y^{NT}} \mathrm{d}k^{IT} - s_{K^{NT}}^{Y^{NT}} \mathrm{d}k^{NT} - s_{L}^{Y^{NT}} \mathrm{d}l \equiv \mathrm{d}t = s_{C}^{Y^{NT}} \mathrm{d}c - \frac{O}{Y^{NT}} \mathrm{d}o + \mathrm{d}z \,, \tag{8}$$

where Y^{NT} is measured gross output, O is the unmeasured output of ICT-complementing investment, and C is the resulting organizational capital. All lower case letters denote log levels, and log difference denotes growth rate. All the input shares are defined with regard to the measured output. The terms to the right of the equal sign state that measured TFP growth exceeds true technology growth by the contribution from the unmeasured capital, C, net of the drag from unmeasured investment (A).

Since we can ignore the business cycle fluctuations of dc in (8), we can derive that the cyclicality of measured TFP, in terms of correlation with measured output growth dy^{NT}, will change as follows:

$$\Delta\rho\left(\mathrm{d}t, \mathrm{d}y^{NT}\right) = \Delta\left[\rho\left(\mathrm{d}z, \mathrm{d}y^{NT}\right)\sigma\left(\mathrm{d}z\right)/\sigma\left(\mathrm{d}t\right)\right] - \Delta\left[\rho\left(\mathrm{d}o, \mathrm{d}y^{NT}\right)\left(\tfrac{O}{Y^{NT}}\right)\sigma\left(\mathrm{d}o\right)/\sigma\left(\mathrm{d}t\right)\right]. \tag{9}$$

For the TFP-output correlation to fall because of the second term—the contribution from intangible investment do—we need at least one of the following possible changes: do and dy^{NT} must become more correlated, do must become more volatile relative to TFP, or the share of intangible investment in a firm's overall activity must increase. An analogous result can be derived for the change in TFP's correlation with primary input growth $\Delta\rho\left(\mathrm{d}t, \mathrm{d}x^{V}\right)$.

To the extent that the volatility change of measured investment is any guide, aggregate business investment has become more volatile relative to output since the mid-1980s (see, for instance, Stock and

[8] The output understatement due to intangible investment, be it related to ICT or not, is qualitatively similar to the more standard and mundane capital adjustment cost that takes the form of forgone market output. Studies such as Basu, Fernald, and Shapiro (2001) have shown that unmeasured work devoted to installing capital can distort measured productivity, for example biasing it downward during the late 1990s because of strong growth in ICT investment.

[9] By comparison, if any fixed cost of production is unmeasured, it similarly understates true output within the period, but it does not distort measured input since no unmeasured capital is formed.

[10] Here we simplify Z to be technology that augments gross output instead of ICT capital directly.

Watson 2002), and thus likely relative to TFP as well. However, there is no evidence that its correlation with output has risen, even though there are reasons to believe that investment in intangible capital is likely more procyclical than investment in measured tangible capital because of greater credit constraints.[11] There is, of course, little data to gauge whether total unmeasured investment, d*o*, has since then constituted a higher share of firm activity. To the extent that we consider the timing of the break in cyclicality as sufficiently strong evidence for the connection between d*o* and observed ICT investment, we can use the share of ICT in total observed investment as a proxy for the importance of d*o*.

In the remainder of this paper, we turn to industry data to examine the patterns of change in the cyclicality of productivity for the private economy as a whole and at the industry level. We then explore whether any of the patterns uncovered are consistent with either or both of the explanations discussed above. As a brief preview, our analysis will reveal patterns, especially in terms of the change after 1984 in the reaction of labor input to technology shocks, that seem to favor the model based on greater labor market flexibility over the model based on greater unmeasured intangible investment.

III. Data and Utilization-Adjusted TFP

Before presenting results, we first describe briefly the data used in the analyses, and how we aggregate industry data to obtain series for the nonfarm business sector as a whole. We then explain how we adjust TFP for unmeasured time-varying utilization of labor and capital.

3.1 Data

We use three sources of data for both the industry-level analysis and the aggregate series constructed using industry data. The primary source is the industry dataset compiled by Dale Jorgenson and his colleagues and made available to the research community.[12] The version used here has been updated from an SIC-based industry classification system to a system more closely aligned with NAICS, and the data have been updated to 2010.[13] "Total industries" in this dataset include not only private

[11] For example, Almeida and Campello (2007) provide empirical evidence of greater countercyclical movements in the cost of external finance for investment in assets that are less tangible, which implies that such investment is more procyclical. Himmelberg and Petersen (1994) present evidence for credit constraints on R&D activities by small firms in high-tech industries and their resulting greater reliance on internal funds.

[12] The latest vintage of their dataset was downloaded on July 17, 2013, from the World KLEMS website http://www.worldklems.net/data/index.htm.

[13] The data are explicitly organized according to the NACE Rev. 2 classification system used by EuroStat and in the

industries but also government enterprises and public administration. Table A.1 in the appendix lists all 31 industries covered in this dataset, plus the seven sub-aggregates, which are italicized. All the analysis will be about growth rates unless otherwise noted. Table A.2 reports the summary statistics of input and output growth rates and factor shares, with the 27 nonfarm business industries in Panel A and all 30 industries (excluding private households with employed persons) in Panel B.

The primary advantage of this dataset is its long time coverage, starting from 1947, whereas other industry datasets, such as those compiled by the Bureau of Economic Analysis (BEA) or the Bureau of Labor Statistics (BLS), all have a break in 1987 because of the changeover from SIC to NAICS. This long time span makes it possible to investigate possible changes in the pattern of cyclical comovements over time, especially if the break date is sometime around the mid-1980s. We complement these data with data on industry characteristics. The data on union membership rate and coverage rate by industry are compiled by Barry Hirsch and David Macpherson; see Hirsch (2008) for details.[14]

We note that all the analyses using these industry data focus only on what we term the nonfarm business sector, defined as private industries excluding farming, forestry, mining, and public administration (that is, industry codes AtB, C, and L in the dataset). This subset comprises 27 industries and approximates the nonfarm business sector in the BLS productivity statistics. The share of all industry VA accounted for by this set of private industries over the sample years is plotted in Figure A.1; their share has risen from slightly below 80 percent in 1947 to a peak of 94 percent in 2000, and 93 percent in 2010. This focus follows the practice in many previous studies, such as BFK (2006). Farming and mining are small, and their fluctuations are driven more by shocks emanating from nature. The public sector's output is measured so poorly that by definition it has zero productivity growth.

In growth rates, LP for each industry i at time t ($\mathrm{d}a_{it}$) is defined as in (1). Aggregate VA growth of the nonfarm business sector, denoted $\mathrm{d}v_t$, is derived as $\mathrm{d}v_t = \sum_i w_i \mathrm{d}v_{it}$, where $\mathrm{d}v_{it}$ is industry-i's VA growth and $w_i = P_{it}V_{it} \big/ \sum_i P_{it}V_{it}$ is i's share in total nominal VA. Aggregate hours input is the simple sum of total hours for each industry. Aggregate LP growth is then simply the difference between aggregate VA and hours growth, as in (1):

cross-country EU KLEMS datasets. For more details of the data, see Jorgenson, Ho, and Samuels (2012).

[14] The data are available online at www.unionstats.com. The data used here were downloaded in March 2013. The union data are organized according to the Census Bureau's CIC industry classification system. This is first mapped into the 2002 NAICS system and then into the KLEMS industry codes.

$$\mathrm{d}a_t = \mathrm{d}v_t - \mathrm{d}h_t = \sum_i w_i \mathrm{d}v_{it} - \mathrm{d}\log\left(\sum_i H_i\right).$$

Aggregate primary input growth, $\mathrm{d}x_t^V$, is defined as $\mathrm{d}x_t^V = s_L^V \mathrm{d}l_t + s_K^V \mathrm{d}k_t$, where s_L^V and s_K^V are the respective shares of labor and capital income in aggregate VA, while dl and dk are the growth rates of aggregate labor and capital input, respectively.

TFP growth at the industry level is first computed as gross output growth (dy_{it}) net of revenue-share-weighted input growth (including materials dm_{it}): (see Appendix I for more details)

$$\mathrm{d}t_{it}^{GO} = \mathrm{d}y_{it} - \mathrm{d}x_{it} = \mathrm{d}y_{it} - \left(s_{Li}\mathrm{d}l_{it} + s_{Ki}\mathrm{d}k_{it} + s_{Mi}\mathrm{d}m_{it}\right).$$

This gross-output-based TFP is multiplied by the Domar weight (that is, the ratio of gross output over VA, both nominal) to obtain VA-based TFP. This VA-based TFP growth is then summed across industries using industry value-added weights, w_i, to compute aggregate TFP growth, dt.

Data on ICT investment and capital stock are compiled by the BLS as part of its productivity database and are available from 1987 to 2012. The latest vintage of data is organized by 2007 NAICS codes and matched to the KLEMS dataset according to the concordance table developed by Jorgenson et al.

The aggregate data series used as demand-side instrumental variables (IVs) for estimations of industry production functions are downloaded from the Haver database. Following BFK (2006), we use two of the Hall-Ramey instruments—oil price and fiscal policy shocks—plus monetary policy shocks, to be detailed later.

3.2 Utilization-Adjusted TFP

Following Basu and Kimball (1997) and BFK (2006), we correct for input utilization by estimating the following first-order approximation to the production function (in growth rates) for each industry to uncover the technology growth (utilization-adjusted TFP) based on gross output:

$$\mathrm{d}y_{it} = \mu_i \mathrm{d}x_{it} + \beta_i \mathrm{d}h_{it} + \mathrm{d}z_{it}, \qquad (10)$$

where dy_{it}, dx_{it}, and dz_{it} are the growth rates of gross output, composite inputs, and technical change, respectively, (as defined in equation (6)). μ_i is the markup on gross output. dh_{it} is the growth of detrended average hours per worker, serving as a proxy for the unobserved variation in both labor effort and capital utilization:

$$\mu_i \mathrm{d}u_{it} = \beta_i \mathrm{d}h_{it} \,. \tag{11}$$

To be conservative and limit the impact of input use to the derived technology series, we use as our baseline the case that constrains all μ_i to 1. This amounts to assuming constant returns to scale (CRS) for all industries.[15] The associated estimates of β_i are reported in Table 1. (Table 2 reports the parameter estimates without the CRS constraint. Appendix III details the estimation procedure and discusses the parameter estimates.) Note that the utilization margin makes a larger contribution to manufacturing TFP (as can be seen in Figure 1): the coefficient is larger for nondurable industries, while average hours are more variable for durable industries. Utilization contributes relatively less to service industries' TFP because service industries have small variations of average hours that also exhibit small output elasticity. This implies more similar cyclical behavior of TFP and technology for service industries, as will be ascertained next. Moreover, as the share of service industries rises, TFP should deviate less from true technical change at the aggregate level.

$\mathrm{d}z_{it}$ and the utilization term, $\beta_i \mathrm{d}h$, are rescaled to a VA basis ($\mathrm{d}z_{it}^V$ and $\mu_i \mathrm{d}u_{it}^V$, respectively) and then summed across industries using industry VA weights to compute their aggregate counterparts, $\mathrm{d}u^V$ and $\mathrm{d}z^V$. Figure 1 plots growth rates of TFP, technology, utilization, etc., for all nonfarm business industries, along with the selected industries and industry groups.

IV. Diminished Procyclicality of Productivity? Aggregate Evidence based on Industry Data

We first examine whether aggregate productivity series constructed using industry data (using the aggregation formulas described above) exhibit patterns of diminished procyclicality similar to those documented using official aggregate data. We consider three measures of productivity—LP, TFP, and utilization-adjusted TFP—for the nonfarm business sector as a whole.

4.1 Diminished Procyclicality of Labor Productivity

We begin with the cyclicality of labor productivity, since this is the cyclical relationship that has been the focus of most previous studies. Given the annual industry data, we focus our analysis on first-

[15] Tests show that industry-level estimates of the μ_i's are each insignificantly different from 1.

differenced (log level) data, which correspond to annual growth rates.[16] Figure 2a plots the annual growth of LP and output (that is, VA) for the nonfarm business sector, along with TFP for comparison. Visual inspection suggests that the correlation pattern between them has changed since sometime in the mid-1980s, here marked by a vertical line at 1984. This date is chosen to be consistent with the choice in Gali and van Rens (2010).[17] All subsequent analyses will divide the sample at 1984.

For comparison, Figure 2b plots the annual growth of TFP and VA against utilization-adjusted TFP. The utilization adjustment is based on estimates of the industry production function (10) imposing the CRS restriction. It is quite clear that once the cyclical fluctuation in utilization is accounted for, adjusted TFP is no longer highly correlated with VA, even before the mid-1980s.[18]

Table 3a reports the correlation between aggregate LP and VA growth for the sample period 1950 to 2007. This is the sample period that will be used as the baseline for the cross-industry analysis in the next section. The first row of Table 3a reports the correlation estimated using bandpass-filtered data (with the cycle defined as two to eight years).[19] Comparable with what Gali and van Rens (2010) find using bandpass-filtered quarterly data, we observe a substantial reduction in the correlation coefficient after 1984, from 0.43 to essentially zero. Two other common filters (with standard parameters) are used for comparison. The decline is a little steeper using the Hodrick-Prescott (HP) filter but noticeably smaller using the Christiano-Fitzgerald (CF 2003) filter (reported in rows two and three of Table 3a, respectively), as will be confirmed in the industry analysis.[20,21] The similarity between the bandpass- and the HP-filtered data is perhaps not surprising, since both have similar gain functions when applied to difference-stationary time series with the standard parameters.[22] We last check the simple first-difference operator.

[16] Gali and van Rens (2010) extract the cyclical component of output and labor productivity using a bandpass filter and the fourth-difference filter applied to (the log level of) quarterly data.

[17] It also coincides with the break date commonly identified in the literature (see, for example, Stock and Watson 2002) when the volatility of aggregate real variables fell significantly. This is, in fact, visible in Figure 2a: LP, TFP, and VA all appear to have become less volatile, and the moderation in VA growth rate is particularly pronounced.

[18] Moreover, in contrast to the other series, purified TFP appears equally volatile before and after the mid-1980s.

[19] Note that the bandpass-filtered data end in 2007 because the filter removes three years at each end of the time series. Therefore, the estimates are identical to those reported for the full sample.

[20] The CF filter is a different finite-sample approximation to the ideal bandpass filter. The version used here is the simplified approach implemented by the Stata command cfitzrw, which is "based on the generally false assumption that the data are generated by a random walk," and found to be nearly optimal.

[21] Canova (1998) considers many other detrending methods, such as the Beveridge-Nelson decomposition and the unobserved component model. It is possible that these other filters may alter the results more, since they amplify different ranges of fluctuations in the frequency domain. But the likelihood is low in light of the findings by Perron and Wada (2009) that, once trend breaks are allowed, detrending models (Bevridge-Nelson and unobserved component) converge, even though they otherwise produce different trend-cycle decompositions.

[22] Between them, the HP filter retains a little more of the high-frequency and the extreme low-frequency movements.

It appears that the annual growth rates of VA and LP have become less correlated basically to the same extent as their cyclical components extracted using the bandpass and the HP filters.[23]

Table 3b reports changes in the correlation between LP and primary inputs (that is, labor and capital) for the same sample period, based on the same set of filters. Arguably, the most notable feature is that the magnitude of the decline is rather similar even though the LP-input correlation was already negative before 1984 (except for the annual growth rate data). So it seems that at least for this set of aggregate annual data over the years 1950 to 2007, the diminished cyclicality of LP is of essentially the same degree whether one evaluates it by the correlation with output or with inputs.

The qualitative pattern again remains basically the same if we extend the second half of the sample to 2010, inclusive of the last, deep, downturn. It is probably not surprising that the considerable fluctuation around the last downturn causes the correlation between LP and VA to decline less since 1984 (see Tables B.2a and B.2b in the appendix). It is also worth noting that the decline in the LP-VA correlation is more similar across different detrending methods with this longer (second half of the) sample.

4.2 Cyclicality of Total Factor Productivity

We apply the same set of methods for trend-cycle decomposition as used above for LP. Table 4a reports the correlation of aggregate TFP with VA growth, while Table 4b reports the correlation with primary input growth, for the baseline sample 1950 to 2007. The overall pattern of the decline is quite similar to their counterparts for LP, although the average magnitude is somewhat smaller.[24] This suggests that the correlation of capital deepening with VA and the relative variance of LP versus TFP have stayed reasonably stable. One notable difference is that, unlike LP's, TFP's correlation with inputs falls more than its correlation with output, as explained in Section 2. The overall similarity between LP and TFP in

---

This turns out not to make much difference in our case. Also, for linear filters such as the bandpass, the directly filtered LP series should be identical by construction to the series derived using filtered output and labor input series. This relationship does not necessarily hold for the HP filter, although they are extremely similar in this case.

[23] This is hinted at by Gali and van Rens's (2010) finding that the decline in correlation is basically as evident in the fourth-differenced quarterly data, which are comparable to first-differenced annual data.

[24] As discussed further later, this is largely due to the steeper decline in the variance of TFP relative to LP. Qualitatively, the same result is confirmed using the full sample of 1950 to 2010 (reported in Tables B.3a and B.3b in the Appendix). Note, however, that TFP is substantially more correlated with both VA and inputs than LP throughout the sample. This is to be expected, because labor input, which gets a much larger negative weight in the definition of LP, is adjusted much more quickly than capital.

terms of the change in cyclicality will be confirmed in the cross-industry analysis in the next section.

4.3 Cyclicality of Utilization-Adjusted Total Factor Productivity

Last, we examine the change in the cyclical comovement between VA and utilization-adjusted TFP for the nonfarm business sector. This helps gauge whether the change in TFP's cyclicality is due more to the lower procyclicality of "true" technology shocks or to the unmeasured contribution from other factors. We again apply the same set of detrending methods as used above. Correlations with VA are reported in Table 5a, while those with primary inputs are in Table 5b. These estimates reveal that the correlation between output and technology shocks has in fact *increased* since 1984, contrary to the pattern for TFP (in Table 4a, and the pattern for LP as well in Table 3a), although the change is significant only for annual growth rates. This indicates that the decline in the correlation between TFP and VA is all due to changes in the cyclical properties of resource utilization.

Interestingly, unlike its relationship with VA, purified TFP has become less correlated with inputs (see Table 5b), although the decline in correlation is clearly smaller (especially for annual growth rates) than the declines for TFP or LP.[25] As we will show, this is mainly because the volatility of technology shocks has risen relative to the volatility of output since 1984. Note that purified TFP and inputs are negatively correlated even before 1984, regardless of the filter considered.

In summary, statistics based on these aggregate series compiled from the industry data confirm findings in previous studies that the cyclical fluctuation of labor productivity has become less correlated with output and input. There is also evidence that the cyclicality of TFP has declined nearly as much. In contrast, data suggest that the cyclical properties of utilization-adjusted TFP have changed little. Virtually all the reduction in the correlation between LP and TFP with output and with inputs is due to changes in input utilization. We next examine the cross-industry pattern of these correlations to explore how plausible the proposed explanations for these stylized facts are.

---

[25] Similar patterns of changes (or the lack thereof) in the correlation of purified TFP with VA and inputs emerge if the full sample (1950 to 2010) is used (see Table B in the appendix).

V. Cross-Industry Patterns of the Changing Cyclicality of Productivity

Industries differ in characteristics that should influence how firms adjust inputs and output, and therefore the degree of mismeasurement in observed inputs or output. Hence, they should differ in how the change of TFP's cyclicality can be decomposed into changes in the cyclicality of technology shocks versus the contribution of unmeasured inputs. Furthermore, the heterogeneity across industries enables better tests of the validity of mechanisms proposed to explain the reduced cyclicality of productivity. It would constitute stronger evidence if the joint implication of a model for multiple variables (such as the change in relative volatility implied by the model in Gali and van Rens 2010) were borne out in the cross section. Moreover, it has been shown (see Basu and Fernald 2002) that aggregate productivity can exceed the weighted average of industry productivity if resources are put to more valuable uses. Using industry data, we can explore whether the less procyclical aggregate productivity is attributable more to the average change at the industry level or to better resource allocation across industries. Decomposing aggregate productivity along these different dimensions can potentially offer additional clues as to the likely reasons for the decline in its procyclicality. As noted above, all the analyses focus on the 27 industries that constitute what we term the nonfarm business sector.

5.1 Changes in the Cyclicality of Labor Productivity across Industries based on Different Filters

This section reports the cross-industry pattern of changes in the cyclicality of LP, based on three of the filters (with the same parameters) used above: HP, CF bandpass, and first-difference. Figures 3a and 3b present scatterplots of changes in the correlation between LP and primary input growth after 1984 versus before 1984 by industry based on the different filters. Table 6 summarizes the cross-industry pattern in these changes, as well as changes in the LP-VA correlation.[26] A few fairly salient cross-industry patterns emerge: 1) the decline in LP's procyclicality is reasonably widespread—observed for the majority of industries—especially in terms of LP's correlation with primary inputs; 2) most service industries show a decline in LP-input correlation, some of which are among the most negative; 3) cross-industry relative sizes of the change are quite similar, especially for LP's correlation with VA, regardless of the filter used.

[26] The cross-industry relationship is slightly less similar if rank correlation is used (available upon request). This is because values of the change are nearly the same across a number of industries, so small differences in value lead to more pronounced differences in ranking.

5.2 Changes in Cyclicality of Productivity: Comparison between LP and TFP

This section compares changes in the cyclicality of two measures of productivity: LP versus TFP. We ascertain that the cross-industry pattern between these two measures is sufficiently similar to justify focusing our attention in all subsequent analyses on TFP, which is more naturally decomposed into the true technology term and terms related to input utilization. Table 7 reports the cross-industry relationship between LP and TFP in terms of the change in their correlation with VA and primary inputs after 1984. A higher correlation coefficient across industries signifies greater similarity between the two measures. It is clear that the change in cyclicality at the industry level is extremely similar using either productivity measure, and regardless of whether cyclicality is measured vis-à-vis VA or primary inputs.

5.3 Changes in Within- versus Cross-Industry Correlations between TFP and Inputs

We first examine a simple decomposition of the correlation between aggregate TFP and input growth, and its post-1984 change, into the portion attributed to weighted average correlations within each industry versus weighted average correlations across industries. Specifically, the aggregate TFP-input correlation can be decomposed as follows:

$$\rho\left(\mathrm{d}t,\mathrm{d}x^{V}\right)=\rho\left(\sum_{i}w_{i}\mathrm{d}t_{it},\sum_{i}\eta_{i}\mathrm{d}x_{it}^{V}\right)$$
$$=\sum_{i}\frac{w_{i}\eta_{i}\sigma\left(\mathrm{d}t_{it}\right)\sigma\left(\mathrm{d}x_{it}^{V}\right)}{\sigma\left(\mathrm{d}t\right)\sigma\left(\mathrm{d}x^{V}\right)}\rho\left(\mathrm{d}t_{it},\mathrm{d}x_{it}^{V}\right)+\sum_{i}\sum_{j\neq i}\frac{w_{i}\eta_{j}\sigma\left(\mathrm{d}t_{it}\right)\sigma\left(\mathrm{d}x_{jt}^{V}\right)}{\sigma\left(\mathrm{d}t\right)\sigma\left(\mathrm{d}x^{V}\right)}\rho\left(\mathrm{d}t_{it},\mathrm{d}x_{jt}^{V}\right),$$

where dt and dx^V are, respectively, the growth rates of TFP and primary inputs as defined above. w_i is industry i's share in total VA, while η_i is its share in total labor and capital cost. These two shares are equal in this dataset because all residual income after subtracting labor and intermediate input cost is attributed to capital, but they can differ if there is pure profit. Terms following the first summation sign measure the contribution to the aggregate correlation from within-industry TFP-input correlations, while the remainder summarizes the contribution from all cross-industry correlations. Note that both sets of terms are weighted averages in that industries with greater VA weights contribute more to the sum.[27] Note also that, with N industries, there are N×(N-1) industry pairs in the cross-industry piece, many more

[27] To be precise, VA shares (w_i's) and cost shares (η_i's) are time-varying, and they in fact covary weakly positively with output growth, as evidenced by the higher growth rate of aggregate TFP if time-varying industry VA shares are used than if the time-series-average shares are used. We ignore these second-order effects in our computation. As a robustness check, we compare results using time-varying versus time-series-average shares and find little difference. This latter treatment is consistent with using the time-series-average shares to approximate the steady-state shares in the production function estimation (of equation (10)), which is interpreted as a first-order approximation.

than in the within-industry piece, which has only N pairs. Therefore, for comparability both terms are normalized to an equal-weighted per-industry-pair basis. Since these per-pair values are rather small, they are scaled up to basis points to facilitate comparison.

Table 8 reports the within- versus cross-industry decomposition of the aggregate TFP-input correlation. First, note that the aggregate TFP-input correlation has fallen more than the unweighted industry average counterpart reported in Table 7, indicating that industries with greater VA weights have experienced larger declines in the TFP-input correlation. This is corroborated by the scatterplots in Figures 3a and 3b: most service industries show a decline in the LP-input correlation, and some are among the most negative. Table 8 shows that before 1984, within- and cross-industry correlations are about equal and thus contribute proportionally to the aggregate correlation. Since 1984, within-industry correlations have fallen noticeably more than their cross-industry counterparts on a per-industry-pair basis, as evidenced by the relative size of the two terms in the last row. The greater contribution of the weighted average within-industry correlation to the lower aggregate TFP-input correlation after 1984 can be construed as consistent with the conjecture of easier or speedier adjustment of factor inputs, since it seems reasonable to expect the more flexible allocation of resources to bring about a larger decline in TFP's correlation with inputs within each industry than across industries.

5.4 Technology or Unmeasured Input Utilization?

This section explores the question of how much of the vanishing procyclicality at the industry level is due to changes in the cyclical properties of the component related to input growth and how much is due to changes in the cyclicality of technology shocks. This extends the finding in Section IV above, based on aggregate series, that once fluctuations in input utilization are adequately accounted for, the derived true technology term is in fact countercyclical. To this end, we use the decomposition of the TFP-input correlation according to equation (7), repeated below (with μ set to 1) for convenience:

$$\Delta\rho\left(\mathrm{d}t,\mathrm{d}x^{V}\right)=\Delta\left[\frac{\sigma(\mathrm{d}u^{V})}{\sigma(\mathrm{d}t)}\right]\rho_{0}\left(\mathrm{d}u^{V},\mathrm{d}x^{V}\right)+\frac{\sigma_{0}(\mathrm{d}u^{V})}{\sigma_{0}(\mathrm{d}t)}\Delta\rho\left(\mathrm{d}u^{V},\mathrm{d}x^{V}\right)$$
$$+\Delta\left[\frac{\sigma(\mathrm{d}z^{V})}{\sigma(\mathrm{d}t)}\right]\rho_{0}\left(\mathrm{d}z^{V},\mathrm{d}x^{V}\right)+\frac{\sigma_{0}(\mathrm{d}z^{V})}{\sigma_{0}(\mathrm{d}t)}\Delta\rho\left(\mathrm{d}z^{V},\mathrm{d}x^{V}\right).$$

Table 9 presents component terms of the decomposition for the nonfarm business sector as well as for four industry groups separately. Panel A reports the overall correlation $\rho(\mathrm{d}t,\ \mathrm{d}x^V)$ and the contribution from utilization ($\mathrm{d}u^V$) versus technical change ($\mathrm{d}z^V$) before 1984 versus after 1984 and the difference.[28] Panel B reports the two correlations on the right-hand side (between du^V, dz^V, and dx^V). Panel C lists volatilities of the three terms before and after 1984, and the ratio between the two subperiods; a ratio less than one means volatility has fallen after 1984.

For the 27 nonfarm private industries as a whole, it is clear that input growth has been negatively correlated with same-period technology shocks throughout the sample years. The absolute size of their correlation declines only slightly after 1984. Nevertheless, technology-related terms account for three-quarters of the decline in TFP's correlation with inputs (0.45 out of 0.61) because its volatility has risen substantially relative to TFP's volatility to yield a fairly negative third term in (7). This volatility ratio has risen as an indirect effect of the lower variance of the utilization term since 1984: technology's volatility remains about the same over time, whereas TFP's volatility has fallen noticeably since 1984 because the volatility of utilization has decreased, stemming partly from the less negative reaction of utilization to technology shocks, as shown below.

At the industry or sector level, the TFP-input correlation has declined for all industries except construction. In particular, the service industries have experienced the greatest reduction. These industries also show the largest decline in technology's correlation with inputs, a decline of nearly the same magnitude as the decline in TFP's correlation with inputs. The similar behavior between TFP and technology in the service industries is the result of relatively small utilization terms—small fluctuations of detrended average hours per worker combined with a comparatively small coefficient β in (11) (that is, the output elasticity of average hours). The change in the cyclicality of technology thus more than accounts for the diminished procyclicality of TFP in the service industries. By comparison, technology contributes about 50 percent of the decline in the TFP-input correlation for nondurable manufacturing, and 60 percent for durable manufacturing.

To further explore changes in the response of inputs and output to technology shocks after 1984, we regress the growth of aggregate private industry output (VA), various components and margins of inputs (including primary inputs, total hours, employment, detrended average hours, and utilization), and TFP on zero-to-four lags of aggregate technology growth and their interactions with the post-1984 dummy variable (D_{post84}), which is equal to one after 1984 and zero otherwise.[29] Given the established fact that output and inputs have become less volatile after 1984 (see, for example, Stock and Watson 2002), we

[28] $\rho(dt,\ dx^V)$ differs slightly from the sum of components because dz is computed using the time-series-average revenue shares of factors, whereas standard TFP is calculated using time-varying weights.

[29] These regressions do not account for the uncertainty concerning the timing of the change, and thus are biased toward finding significant breaks.

also allow the volatility of residuals to change using a maximum likelihood estimator.[30] Specifically, we estimate:

$$\mathrm{d}g_t = \alpha_g + \sum\nolimits_{s=0}^{4} \delta_s \mathrm{d}z_{t-s} + D_{post84} \sum\nolimits_{s=0}^{4} \phi_s \mathrm{d}z_{t-s} + \varepsilon_{gt},$$

$$\sigma\left(\varepsilon_{gt}\right) = \alpha_\varepsilon + \eta D_{post84}, \tag{12}$$

where $\mathrm{d}g_t$ is the aggregate output or input variable of interest, and ϕ_s measures whether the coefficients on dz and its lags have changed significantly since 1984. These regressions can be interpreted as impulse response functions à la Jordà (2005) to the extent that the technology series represent correctly identified shocks.

The results of these regressions are presented in Table 10. Arguably the most notable feature is that detrended average hours respond as negatively to same-year technology shocks after 1984 as earlier, whereas utilization responds less negatively after 1984. The latter change (from -1.215 before 1984 to -0.718 after 1984) is statistically significant although the response of utilization remains significantly negative after 1984. This change is also partly responsible for the lower variance of utilization after 1984, given that the variance of technology shocks stays the same over both subperiods. The part of utilization's variance that is uncorrelated with technical change has also fallen since 1984, as shown by the significantly negative estimate of η in (12). This is likely due to a lower variance of demand shocks since 1984. The response of employment and hence of total hours to technology shocks also turns less negative after 1984, although neither change is significant, nor is employment's response in either subperiod. Nevertheless, it is worth noting that this extensive margin of labor input now moves less, while the intensive margin of average hours moves essentially the same amount in response to a given contemporaneous technology shock.

Since utilization is just detrended average hours rescaled by its output elasticity β (with μ restricted to 1), the difference in their behavior means that those industries with a larger output elasticity of average hours have become less important in the economy after 1984. The parameter estimates reported in Table 1 indicate that these are the manufacturing industries. The less contractionary reaction of utilization, combined with equally volatile technology shocks, causes TFP, which is their sum, given μ equal to 1, to switch from a negative response to contemporaneous technology shocks before 1984 to a

[30] We also estimated an alternative set of regressions where standard errors are computed using the bootstrapping method in order to correct for the generated regressor problem due to the fact that the technology shocks are themselves estimated. These regressions, however, do not allow the residual variance to change. Nevertheless, the coefficients on dz and its lags are qualitatively the same.

positive response of about the same magnitude after 1984.[31] This renders TFP less correlated with inputs in the same period, since inputs now still respond negatively, albeit somewhat less so, to same-period technology shocks. In the subsequent four periods, the response of average hours remains economically and statistically the same. The response of utilization actually turns a little less positive, meaning that since 1984 utilization does not rebound as much over the next four years.

We then examine the post-1984 change in the response of utilization to same-period technology shocks at the level of each individual industry, which is proportional to the response of average hours. Table 11 reports the summary statistics of the coefficient estimates from 27 industry-level regressions as specified in (12), with utilization being the dependent variable. Note that the mean here is the unweighted average of industry-specific coefficients, whereas the coefficients in column (6) of Table 10 can be thought of as the industry-VA-weighted average. Table 11 shows that the simple cross-industry average of utilization's response to contemporaneous technology shocks has in fact become more negative. This is opposite to the change for the nonfarm business sector as a whole, which assigns greater weights to industries with larger nominal VA. This contrast indicates that those industries with higher VA weights, mostly service industries, have seen their average hours per worker react more positively to same-year technology shocks since 1984. This is consistent with the result reported for service industries in Table 9 that the utilization term by itself turns the TFP-input correlation more positive after 1984. By comparison, the cross-industry average responses in subsequent periods are mostly the same before and after 1984.

As a robustness check, we estimate the same set of regressions using technology shocks derived using the production-function coefficients reported in Table 2, which do not constrain the returns to scale parameter. The regression output is displayed in Table B.4. The main results are qualitatively the same as those in Table 10. That is, average hours react about as negatively, while utilization reacts less negatively to same-period technology shocks. In the following four periods, average hours again react about the same, while utilization rebounds somewhat less. Output responds more positively contemporaneously, although the overall reaction is insignificant, but a little more negatively in the following periods. Neither employment nor total hours respond significantly differently in any of the periods.

Hence, the overall pattern is that utilization has become less contractionary with regard to same-period technology shocks, but its rebound afterward has also been smaller since the mid-1980s. At the

[31] If dz were the single regressor, then the coefficient of regressing dt on dz could be written as δ_{dt} = cov(dt, dz)/var(dz) = cov(du+dz, dz)/var(dz) = 1+cov(du, dz)/var(dz) ≡ 1+ δ_{du}, where δ_{du} is the coefficient of regressing utilization on dz. Hence, with $0 > \delta_{du} > -1$, δ_{dt} is positive. This relationship is not exact when there are multiple regressors, but the logic remains valid.

same time, employment also reacts a little less negatively, while average hours per worker react as negatively to technology shocks. These reactions still constitute noticeable departures from the standard RBC model. Moreover, they are not fully consistent with the explanation proposed by Gali and van Rens (2010), which emphasizes reductions in the cost of adjusting employment but not the intensive margin of effort. In actuality, the more readily measured intensive margin is average hours per worker, which is, to a first order, proportional to effort under general conditions, so we expect firms to utilize the hours per worker margin less than the employment margin if it is the latter's adjustment cost that has fallen.

One possible reason that the sensitivity of employment to technology shocks has diminished relative to that of average hours is that the persistence of technology shocks may have risen. The relative use of external versus internal margins also depends on the persistence of shocks, and technology shocks are contractionary in the same period. More persistent technology shocks imply that it is now optimal for firms to cut total hours less through layoffs and more through shorter hours per worker when the firms enjoy a technology improvement, since they expect more improvements going forward and thus anticipate the need to hire more workers eventually. This logic is analogous to that shown in Ramey and Vine (2006) but with the opposite sign.[32] Regression analysis, reported in Table 12, indeed finds an increase in the persistence of technology shocks after 1984. Specifically, the following regression, which imposes a first-order moving average process on the error term and includes a post-1973 dummy variable for a lower growth rate, finds β_1 (on the first autoregressive coefficient interacted with the post-1984 dummy variable) significantly positive:[33]

$$\mathrm{d}z_t = \alpha + \alpha_1 D_{post73} + \beta \mathrm{d}z_{t-1} + \beta_1 \mathrm{d}z_{t-1} D_{post84} + e_t - e_{t-1}. \qquad (13)$$

The private sector's reaction to technology shocks is also influenced by the degree to which the monetary authority accommodates the shocks. The less negative reaction of total hours to technology shocks in the same year after 1984 suggests that monetary policy has become more accommodative of technology shocks, as argued by Gali et al. (2003), although the change is not statistically significant. Monetary accommodation also seems to have become more persistent, possibly in response to the greater persistence of technology shocks. To wit, prices fall as much (albeit insignificantly) in the same year in

[32] They find that automakers utilize the intensive margin relatively more to adjust inputs after 1984 because demand shocks are less persistent, making it less worthwhile to pay the adjustment cost for the extensive margin.
[33] This regression specification is derived based on the assumption that the (log) level of technology (z) is stationary around a deterministic trend: $z_t = \alpha t + \varepsilon_t$, and $\varepsilon_t = \beta\varepsilon_t + e_t$. Then, we can write d$z$ as $\mathrm{d}z_t = \alpha(1-\beta) + \beta \mathrm{d}z_t + e_t - e_{t-1}$. We also tried estimating a similarly specified regression of log levels of z, and the counterpart to β_1 is again positive.

response to a positive impulse in technology after 1984 but react less negatively in the next four years (significantly so in the second and the third year), as shown in the last column of Table 10.[34]

Our finding that there is little change in the correlation between true technology and inputs at the aggregate level, once variations in unmeasured inputs are accounted for, indicates that an increase in the importance of (cyclical) intangible investment is not needed to explain the diminished procyclicality of LP and TFP. On the other hand, the noticeable reduction in the technology-input correlation among service industries can potentially mean that intangible investment has played a role, to the extent that unmeasured investment related to ICT is more important to industries such as professional business services. The greater persistence of technology shocks may also reflect, in part, the greater importance of unmeasured investment. This is because fluctuations in such activities are likely to persist over multiple periods, causing our utilization-adjusted TFP to become more persistent as well, since corrections for unmeasured input use are unlikely to fully account for the unmeasured internal output.

5.5 Change in Cyclicality of Technology or Resource Allocation?

At the aggregate level, TFP can differ from technology not only because of unmeasured input utilization but also because of changing efficiency of resource allocation due to frictions in output or input markets that preclude perfect mobility of resources across firms or industries, as shown in Basu and Fernald (2002). In this section, we decompose the TFP of the nonfarm business sector and examine the relative contribution of technology versus cross-industry resource allocation to the post-1984 change in TFP's cyclicality. This can help to shed light on the likely causes of the change. For instance, if more flexible input and output markets after 1984 improve the allocation efficiency relatively more during recessions, when the markets tend to suffer less efficient allocations than during expansions, then better allocations can partly explain the less procyclical TFP. Note that we can only uncover the effect of allocations across industries with industry data; any effect of within-industry allocations is already reflected in industry TFP. Hence, even a small cross-industry allocation effect can be consistent with the proposed story of more flexible adjustment of resources to the extent that we think the effect should manifest first and more strongly at the individual-industry level, as opposed to across industries.

The relationship between aggregate TFP ($\mathrm{d}t$) and aggregate technology ($\mathrm{d}z^V$) can be expressed as follows (see Appendix I for details of the derivation and the definition of each term):

---

[34] The implicit VA deflator is the only variable that shows a significantly lower growth rate after 1984, reflecting the steady disinflation since the mid-1980s through the 1990s, and even in the early 2000s.

$$\mathrm{d}t_t = \left[\left(\bar{\mu} - 1 \right) \mathrm{d}x_t^V + \mathrm{d}\bar{u}_t^V + R_{M,t} \right] + R_{\mu,t} + \bar{\mu} \left(R_{L,t} + R_{K,t} \right) + \mathrm{d}z_t^V , \tag{14}$$

where dt, dx^V, and dz^V are the growth of aggregate TFP, measured primary inputs, and technical change, respectively. $\bar{\mu}$ is the VA-weighted average of markups on gross output. $\mathrm{d}\bar{u}_t^V$ denotes the average contribution from unmeasured inputs.[35] R_μ denotes the contribution from the distributions of production across firms with different markups, while R_M, R_K, and R_L denote contributions from allocations of intermediate, capital, and labor inputs to firms, with different shadow prices for the respective inputs.

The first term in equation (14) measures the contribution to aggregate productivity from growth in primary inputs when there is imperfect competition, in which case the contribution of intermediate inputs to gross output exceeds their share in revenue by the gross-output markup. The contribution to aggregate productivity from reallocations of capital and labor is also scaled up by the Domar weights (industry gross output normalized by aggregate VA). The intuition of the reallocation terms is that when more production shifts to firms or industries with higher markups, or higher shadow values of inputs, the overall economy generates more output (measured in units of the numeraire) without more inputs — becomes more productive — even without any technological improvements.

Since what determines the size of the allocative efficiency terms is the shadow price of inputs, which may not exactly equal the observed price at any point in time, we follow Basu and Fernald (2002) and impute the sum of these terms as the residual term after netting out aggregate technology, plus the contribution of measured and unmeasured primary inputs, that is:

$$R \equiv R_\mu + R_M + \bar{\mu} \left(R_L + R_K \right) = \mathrm{d}t - \left(\bar{\mu} - 1 \right) dx^V - \mathrm{d}\bar{u}^V - \mathrm{d}z^V . \tag{15}$$

As an alternative estimate, we also calculate $R_{M,}$ using data and parameter estimates, assuming that observed prices of intermediate inputs are closely aligned with their true shadow value.

Decomposition of aggregate TFP according to (14) can be carried out using estimates of μ, μdu, and dz^V derived above. Table 13 presents the result based on the CRS production function coefficients reported in Table 1. It is obvious from equation (14) that with μ constrained to 1, all of the allocative efficiency terms except two—R_L and R_K—disappear. Hence, it is not surprising that the allocation terms contribute only about 10 percent to the change in TFP's correlation with inputs. Instead, the bulk is accounted for by utilization, and especially technology. The limited role of allocation terms is similar for TFP's correlation with output. In contrast, technology in fact contributes the wrong way, being more than offset by the outsized decline in utilization's correlation with VA.

[35] Basu and Fernald (2002) in fact do not explicitly correct for such cyclical mismeasurement because their focus is the relationship between aggregate productivity and aggregate technology, although they recognize the importance of utilization adjustments, as shown in BFK (2006).

It is probably also not surprising that once we relax the CRS constraint, the allocation terms become much more important contributors to the lower correlations between TFP and inputs as well as output, as can be seen in Table 14. It is interesting to consider this result in the context of findings from previous studies using establishment- and firm-level data that reallocation within each industry dwarfs reallocation across industries (see Foster, Haltiwanger, and Krizan 2001 for a review). Our industry-level data can only uncover the latter. It warrants further analysis to understand whether and, if so, why inter-industry reallocations matter to this extent for the cyclical behavior of productivity despite their much smaller magnitude than intra-industry reallocations. Given the uncertainty surrounding the production function coefficient estimates, however, we would interpret the results in Table 14 with caution. It seems more sensible to consider the sum of the contribution from utilization and allocation terms, given the pattern that an increase in returns to scale tends to reduce the importance of utilization. Then, combining the interpretation of these two sets of estimates, utilization and allocation together account for 25 to 50 percent of the decline in the correlation of TFP with inputs.

5.6 Cross-Industry Evidence for Greater Labor Market Flexibility

We now examine the extent to which the relationship between the change in TFP's cyclicality and changes in other attributes implied by the explanation proposed by Gali and van Rens (2010) is borne out in the cross-section of industries. In particular, Gali and van Rens's (2010) model implies a strong negative relationship between TFP's cyclicality and the relative volatility between inputs and output: the more flexibly adjustable, and hence relatively more volatile inputs become vis-à-vis output, the lower the TFP-input correlation. In addition, to the extent that we think the change in union membership is a reasonable indicator of changes in the flexibility of labor institutions, we should expect larger declines in union membership to be associated with more pronounced reductions in the procyclicality of TFP.

Figure 4 plots the post-1984 change in TFP's correlation with primary input growth (on the y-axis) against the post-1984 change in the total-hours-over-VA volatility ratio (on the x-axis). There is a robust negative relationship across industries: the more volatile an industry's total labor hours relative to its VA, the less correlated is its TFP with inputs. The slope coefficient is fairly significant if we regress the latter on the former.[36] Figure 5 plots the analogous relationship with employment substituting for total hours. It is remarkable how similar the two relationships are, although not surprising, since most of the variation in total hours is accounted for by changes in employment. Another notable feature is the

[36] It is not corrected for the generated regressor problem.

substantial degree of dispersion across industries in terms of the change in the relative volatility of VA to labor input even though, on average, the latter has become somewhat more volatile. Note that all of these are unconditional relationships, reflecting the joint outcome of institutional changes subject to both demand and technology shocks.

The cross-industry pattern reflected in these two figures provides support for the proposal that increased flexibility in labor markets can account for the diminished procyclicality of productivity. On the other hand, the change in TFP's cyclicality appears to be unrelated to the change in the relative volatility of employment to average hours per worker, as shown by Figure 6. Along with the earlier finding of more persistent technology shocks after 1984, this suggests that changes in the persistence of shocks may be the main reason for the relative change in firms' use of the intensive versus the extensive margin of labor input. To the extent that we still think more flexible labor markets are part of the explanation, this also suggests that the reforms have likely made it less costly to alter both margins of labor input.

For more direct evidence of the impact of changes in labor market institutions on the cyclical properties of productivity, we examine the cross-industry pattern of the change in the rate of union membership between 1983 and 2007 compared with the change in the industry's TFP-input correlation. As shown in Figure 7, the share of union members in total employees has fallen in virtually every industry. However, there does not appear to be an obvious relationship between the cumulative change in union membership rates since 1983 and the change in the TFP-input correlation across industries.[37] On the other hand, if we restrict the sample to those industries where union membership rates have declined more than 10 percentage points between 1983 and 2007, we find a significant positive relationship. This suggests that the decline in union membership needs to be sufficiently large to produce a measureable effect. Relatively small declines in union representation may reflect random variations rather than a systematic decline in the influence of unions, and thus not alter the cyclicality of TFP. In sum, the evidence is less than decisive.

5.7 Cross-Industry Evidence for Greater Intangible Investment

Last, we explore whether the cross-industry pattern of the change in TFP's cyclicality is consistent with a model in which unmeasured investment has become more important since the mid-1980s. We focus on approximating intangible investment associated with ICT capital, because of the timing of the

[37] The pattern is rather similar if, instead of membership rate, we use union coverage rate.

change, as argued in Section II. From equation (9), if we assume that the distortion due to unobserved investment was small for all industries prior to 1984, then we can use the post-1984 values of the terms in the second bracket, that is, $\rho\left(\mathrm{d}o, \mathrm{d}x^{V}\right)\left(\frac{O}{Y^{NT}}\right)\sigma\left(\mathrm{d}o\right)/\sigma\left(\mathrm{d}t\right)$, to approximate the change in the contribution of Δa.

If we assume that the depreciation rate of ICT-related intangible capital is fairly low because it is generally perceived to be improved production processes, then the growth rate of the related investment do equals $\left(\frac{C}{O}\right)\left[\mathrm{d}k_t^{IT} + \upsilon \mathrm{d}p_t^{IT} - \left(\mathrm{d}k_{t-1}^{IT} + \upsilon \mathrm{d}p_{t-1}^{IT}\right)/(1+g)\right]$, where $\mathrm{d}k^{IT}$ is the growth rate of ICT capital, $\mathrm{d}p^{IT}$ is the change in its price relative to that of intangible capital, υ is the elasticity of substitution between ICT and the intangible capital, and g is the steady-state growth rate of technology. If we assume that movements in relative prices contain mostly an aggregate component, then we can rely mainly on the quantity variable, $\mathrm{d}k^{IT}$, to approximate do at the industry level. Together, we have the following approximation for the contribution of intangible investment to the change in the correlation with TFP:

$$\Delta\rho\left(\mathrm{d}t, \mathrm{d}x^{V}\right) = -\rho\left(\mathrm{d}k_t^{IT} - \mathrm{d}k_{t-1}^{IT}/(1+g), \mathrm{d}x^{V}\right)\left(\frac{C}{Y^{NT}}\right)\sigma\left(\mathrm{d}k_t^{IT} - \mathrm{d}k_{t-1}^{IT}/(1+g)\right)/\sigma\left(\mathrm{d}t\right). \qquad (16)$$

We approximate g with each industry's sample average TFP growth rate, and C/Y^{NT} with the share of ICT investment in total investment.[38] To match the sample period of the TFP correlation comparison, we use capital growth from 1988 to 2007 to compute the statistics in (16).

Figure 8 plots the estimate of (16) by industry on the x-axis against the post-1984 change on TFP's correlation with primary input growth on the y-axis. These would be positively related if intangible investment has been an important contributor to the diminished TFP-input correlation, assuming the proxy is reasonably accurate. It is clear that there is no discernable relationship between the two variables. The estimate of (16) seems to contain valid information about the contribution of ICT capital, since the foremost outlier in terms of importance of ICT is industry 74, which encompasses all the business and professional services, consistent with our prior understanding. Nevertheless, it may still be a poor approximation of the amount of general intangible investment by each industry and its impact on the cyclicality of measured TFP. Better data are needed to explore this mechanism further.

In short, there is evidence along some dimensions supporting the proposed explanation that more flexible labor arrangements are at least partly responsible for the decline in the procyclical behavior

[38] This approximation may be too low on average in terms of the level because the capital stock likely exceeds output, but it may be a reasonable proxy for the cross-industry relationship of the true ratio, which is the comparison here.

of productivity. However, it seems that this proposed mechanism needs to be interpreted more broadly to encompass both the extensive and the intensive margins of labor input to be more consistent with the empirical facts. Moreover, changes in the volatility and persistence of technology as well as demand shocks have likely played an important role in diminishing the procyclicality of productivity.

VI. Conclusion

This study attempts to gain a better understanding of the forces underlying the diminished procyclicality of aggregate productivity by analyzing changes in the cyclical properties of productivity at the industry level. This should be useful for modeling business cycle dynamics. A good grasp of the cyclicality of productivity, and in turn a more accurate trend-cycle decomposition of actual growth, is also important for monetary policymakers to enable them to correctly gauge the amount of slack in the economy.

We find that service industries have shown the greatest decline in the correlation of productivity with output and inputs since the mid-1980s. Partly for this reason, the correlations within each industry have fallen more than the correlations across industries. Applying a method from previous studies, we correct total factor productivity for unmeasured input utilization to evaluate the relative contributions of technical change and utilization to the change in productivity's cyclical dynamics. We discover that the cyclicality of technology shocks has changed little: they have remained contractionary within the first year throughout the sample period. The main reason for TFP's lower correlations with output and inputs is that the technology term accounts for a larger share of TFP's correlations with these variables after the mid-1980s than earlier because the volatility of utilization has fallen, so the volatility of technology shocks has risen relative to that of TFP.

We find evidence, at both the aggregate and the industry levels, that since the mid-1980s average hours per worker *contract* in response to a positive technology shock in the same period as much, if not more, than earlier. On the other hand, aggregate utilization, which is a weighted average of hours per worker scaled by its output elasticity at the industry level, now contracts less in reaction to a positive technology shock. These two variables exhibit different changes in behavior from each other at the aggregate level because manufacturing industries, whose cyclical fluctuations of utilization exceed those of the service industries, have seen their share in the economy shrink. Utilization combined with the greater contribution from the technology term leads overall TFP to react more positively since the mid-1980's to technology shocks, and thus become less correlated with inputs and output.

We also find that, for the aggregate nonfarm private economy, employment and thus total labor input contract less than formerly, albeit insignificantly so, in response to a positive technology shock within the same period. This can be construed as evidence supporting the notion that monetary policy has improved its accommodation of technology shocks. The fact that employment has become less, not more, responsive than hours per worker to technology shocks since the mid-1980s can be explained by the finding that such shocks have become more persistent. It is, however, inconsistent with the explanation based purely on lower hiring and firing costs.

On the other hand, there is a robust relationship across industries between the decline in the correlation of TFP with inputs and output, and the relative increase in the volatility of employment and total hours vis-à-vis value added. Moreover, the unconditional volatility of employment has risen relative to that of hours per worker since 1984. These findings together suggest that whatever reforms have enhanced the flexibility in labor markets have likely enabled firms to reduce the cost of adjusting both the extensive and the intensive margins of labor. At the same time, the more flexible labor market seems to have mostly led to more efficient input adjustments within each individual industry, since when we decompose aggregate TFP into technology, utilization, and resource allocation terms, we find that the latter two combined can account for only about one-quarter of the reduction in the procyclicality of TFP.

To the extent that we believe these findings constitute reasonable evidence of greater flexibility in the labor market, which is a structural change and thus should be long lasting, these findings imply that policymakers should down-weight the performance of productivity during downturns in their estimates of the underlying trend growth rate. It also leads to the question of how to reconcile the greater flexibility in the labor market with jobless recoveries. Berger (2012) provides a plausible explanation, but this issue warrants further analysis.

In contrast, we find no evidence that the increased importance of intangible investment, in particular the type associated with information technology, helps to explain the decline in the cyclicality of TFP. The absence of evidence does not necessarily constitute strong evidence of absence in this case, since the approximation we have constructed for intangible investment may well be too noisy. Besides, the finding that service industries are among the greatest contributors to the diminished procyclicality of productivity suggests that ICT-related intangible investment may have played a role. More and better data are seriously needed to further explore this potential explanation. If intangible investment such as

R&D is indeed highly cyclical, then the Great Recession and the ensuing weak recovery may have grave implications for the pace of technological progress in the medium or even long term.

References

Almeida, Heitor, and Murillo Campello. 2007. "Financial Constraints, Asset Tangibility, and Corporate Investment." *Review of Financial Studies* 20 (5): 1429–1460.

Barnichon, Regis. 2010. "Productivity and Unemployment Over the Business cycle." *Journal of Monetary Economics* 57: 1013–1025.

Basu, Susanto. 1996. Cyclical productivity: Increasing returns or cyclical utilization? *Quarterly Journal of Economics* 111 (August): 719–751.

Basu, Susanto, and John Fernald. 1997. "Returns to scale in U.S. manufacturing: Estimates and implications." *Journal of Political Economy* 105 (April): 249–283.

Basu, Susanto, and Miles Kimball. 1997. "Cyclical Productivity with Unobserved Input Variation." NBER working paper #5915.

Basu, Susanto, and John Fernald. 2002. "Aggregate Productivity and Aggregate Technology," *European Economic Review* 46: 963–991.

Basu, Susanto, and John Fernald. 2001. "Why is Productivity Procyclical? Why Do We Care?" In *New Development in Productivity Analysis*, eds. Charles R. Hulten, Edwin R. Dean, and Michael J. Harper. 224–296. NBER. Available at http://www.nber.org/chapters/c10128.

Basu, Susanto, John Fernald, and Matthew D. Shapiro. 2001. "Productivity Growth in the 1990s: Technology, Utilization, or Adjustment?" *Carnegie-Rochester Conference Series on Public Policy* 55 (2001) 117–165.

Basu, Susanto, John G. Fernald, Nicholas Oulton, and Sylaja Srinivasan. 2004. "The Case of the Missing Productivity Growth, or Does Information Technology Explain Why Productivity Accelerated in the United States but Not the United Kingdom?" In *NBER Macroeconomics Annual 2003*, ed. Mark Gertler and KennethR ogoff, 9–63. Cambridge: MIT Press.

Basu, Susanto, John Fernald, and Miles Kimball. 2006. "Are Technology Improvements Contractionary?" *American Economic Review* 96(5): 1418–1448.

Berger, David. 2012. "Countercyclical Restructuring and Jobless Recoveries," working paper, Yale University.

Brynjolfsson, Eric, and Lorin M. Hitt. 2000. "Beyond Computation: Information Technology, Organizational Transformation and Business Performance." *Journal of Economic Perspectives*,

Brynjolfsson, Eric, and Lorin M. Hitt. 2003. "Computing Productivity: Firm-Level Evidence." *Review of Economics and Statistics* 85(4): 793–808.

Christiano, Larry J., and T. J. Fitzgerald. 2003. "The Band Pass Filter." *International Economic Review* 44: 435–465.

Christiano, Larry J., Martin Eichenbaum, and Charles L. Evans. 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy* 113(1): 1–45.

Elsby, Michael W. L., Bart Hobijn, and Ayşegül Şahin. 2013. "The Decline of the U.S. Labor Share." *Brookings Panel on Economic Activity*.

Fernald, John G. 2007. "Trend Breaks, Long-Run Restrictions, and Contractionary Technology Improvement." *Journal of Monetary Economics*. 54: 2467–2485.

Fernald, John G. 2012. "A Quarterly Utilization-Adjusted Series on Total Factor Productivity." Manuscript. http://www.frbsf.org/economics/economists/jfernald.html. Data supplement at http://www.frbsf.org/economics/economists/jfernald/quarterly_tfp.xls.

Foster, Lucia, John C. Haltiwanger, and C. J. Krizan. 2001. "Aggregate Productivity Growth: Lessons from Microeconomic Evidence." *New Developments in Productivity Analysis*, Charles R. Hulten, Edwin R. Dean, and Michael J. Harper, eds., University of Chicago Press.

Francis, Neville, and Valerie A. Ramey. 2005. "Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited." *Journal of Monetary Economics* 52(8): 1379–1399.

Gali, Jordi. 1999. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" *American Economic Review* 89(1): 249–271.

Gali, Jordi, J. David Lopez-Salido, and Javier Valles. 2003. "Technology Shocks and Monetary Policy: Assessing the Fed's Performance." *Journal of Monetary Economics* 50(4): 723–743.

Galí, Jordi, and Luca Gambetti. 2009. "On the Sources of the Great Moderation." *American Economic Journal: Macroeconomics*, 1(1): 26–57.

Gali, Jordi, and Thijs van Rens. 2010. "The Vanishing Procyclicality of Labor Productivity." CEPR Discussion Paper #DP9853.

Gordon, R. J. 2010. "Okun's Law, Productivity Innovations, and Conundrums in Business Cycle Dating." *American Economic Review: Papers and Proceedings* 100(2).

Hall, Robert E. 1988. "The Relation Between Price and Marginal Cost in U.S. Industry." *Journal of Political Economy* 96: 921–947.

Hall, Robert E. 1990. "Invariance Properties of Solow's Productivity Residual. In: Diamond, P., ed., *Growth, Productivity, Employment.* MIT Press, Cambridge, MA.

Hamilton, James D. 1996. "This Is What Happened to the Oil Price-Macroeconomy Relationship." *Journal of Monetary Economics* 38(2): 215–220.

Helpman, Elhanan, and Manuel Trajtenberg. 1998. *General Purpose Technologies and Economic Growth* MIT press.

Himmelberg, Charles P., and Bruce C. Petersen. 1994. "R & D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries." *Review of Economics and Statistics* 76(1): 38–51.

Hirsch, Barry T. 2008. "Sluggish Institutions in a Dynamic World: Can Unions and Industrial Competition Coexist?" *Journal of Economic Perspectives* 22(1): 153–176.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review*, 95(1): 161–182.

Jorgenson, Dale, Mun Ho, and David Samuels. 2012. "Information Technology and U.S. Productivity Growth." In Matilde Mas and Robert Stehrer, eds., *Industrial Productivity in Europe* Northampton Massachusetts, Edward Elgar, 34–65.

Kuttner, Kenneth N. 2001. "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market." *Journal of Monetary Economics* 47(3): 523–544.

McGratten, Ellen R. and Edward C. Prescott. 2007. "Unmeasured Investment and the Puzzling U.S. Boom in the 1990s." NBER working paper 13499.

McGratten, Ellen R. and Edward C. Prescott. 2012. "The Labor Productivity Puzzle." Federal Reserve Bank of Minneapolis working paper 694.

Nucci, F., and M. Riggi. 2009. "The Great Moderation and Changes in the Structure of Labor Compensation." Unpublished manuscript.

Oliner, Stephen D., Daniel E. Sichel, and Kevin J. Stiroh. 2007. "Explaining a Productive Decade." *Brookings Papers on Economic Activity*, V2007 (1): 81–137.

Pierre Perron, and Tatsuma Wada. 2009. "Let's Take a Break: Trends and Cycles of U.S. Real GDP." *Journal of Monetary Economics* 56: 749–765.

Ramey, Valerie A. 1989. "Inventories as Factors of Production and Economic Fluctuations." *American Economic Review* 79 (June): 338–354.

Ramey, Valerie A., and Daniel J. Vine. 2006. "Declining Volatility in the U.S. Automobile Industry." *American Economic Review* 96(5): 1876–1889.

Ramey, Valerie A. 2011. "Identifying Government Spending Shocks: It's all in the Timing." *Quarterly Journal of Economics* 126 (1): 1–50.

Romer, Christina D., and David H. Romer. 2004. "A New Measure Of Monetary Shocks: Derivation and Implications." *American Economic Review*, 94(4): 1055–1084.

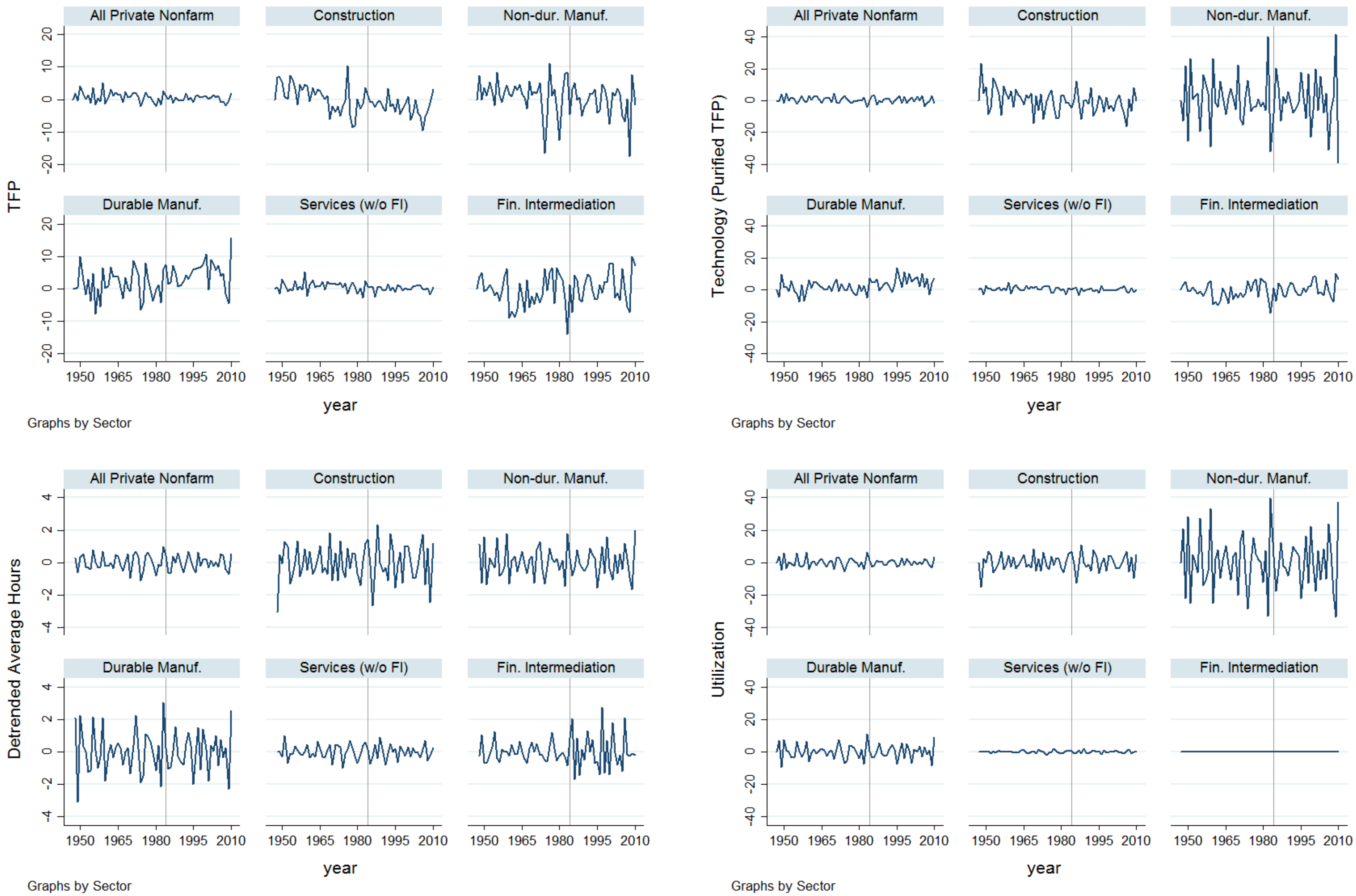
Rotemberg, Julio J., and Michael Woodford. 1995. "Dynamic General Equilibrium Models with Imperfectly Competitive Product Markets." In *Frontiers of Business Cycle rResearch*, ed. Thomas F. Cooley, 243–293. Princeton: Princeton University Press.

Stiroh, K. J. 2009. "Volatility Accounting: A Production Perspective on Increased Economic Stability." *Journal of the European Economic Association* 7 (4): 671–696.

Stock, James H., and Mark W. Watson. 2002. "Has the Business Cycle Changed and Why?" *NBER Macroeconomics Annual*. 17: 159–218.

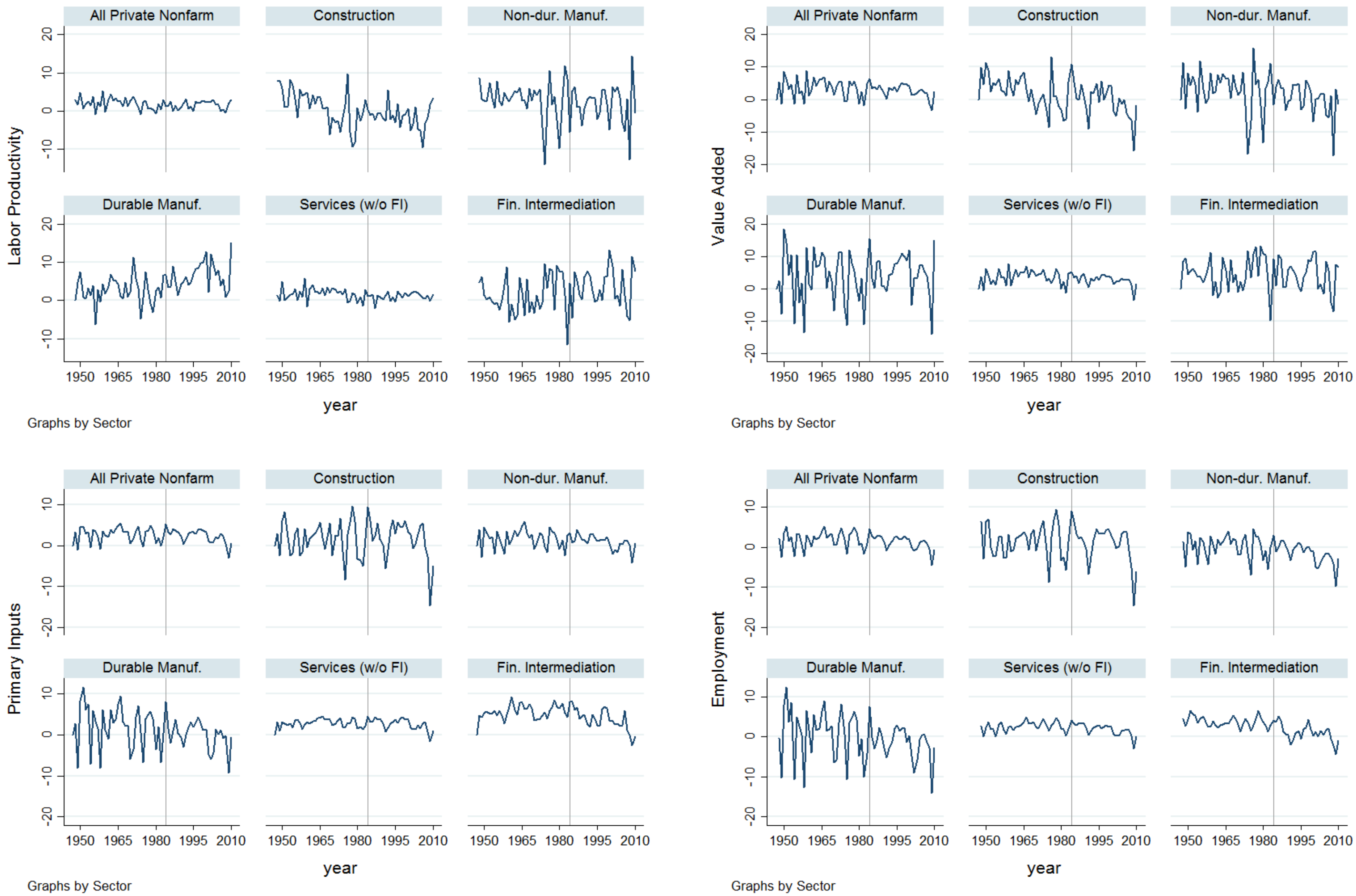
Wolff, Edward N. 2002. "Productivity, Computerization, and Skill Change." National Bureau of Economic Research Working Paper 8743.

Figure 1. Productivity, technology, value added, and primary inputs of all nonfarm business industries and selected industry groups



Notes: All the variables are growth rates in percentages. The grey vertical line marks 1984. Utilization is restricted to zero for Financial Intermediation.

Figure 1. (continued) Labor productivity, value added, and primary inputs of all nonfarm business industries and selected industry groups



Notes: All the variables are growth rates in percentages. The grey vertical line marks 1984. Utilization is restricted to zero for Financial Intermediation.

Figure 2a. Annual growth rate of labor productivity, total factor productivity, and value added
(Aggregate for the nonfarm business sector constructed using industry data)

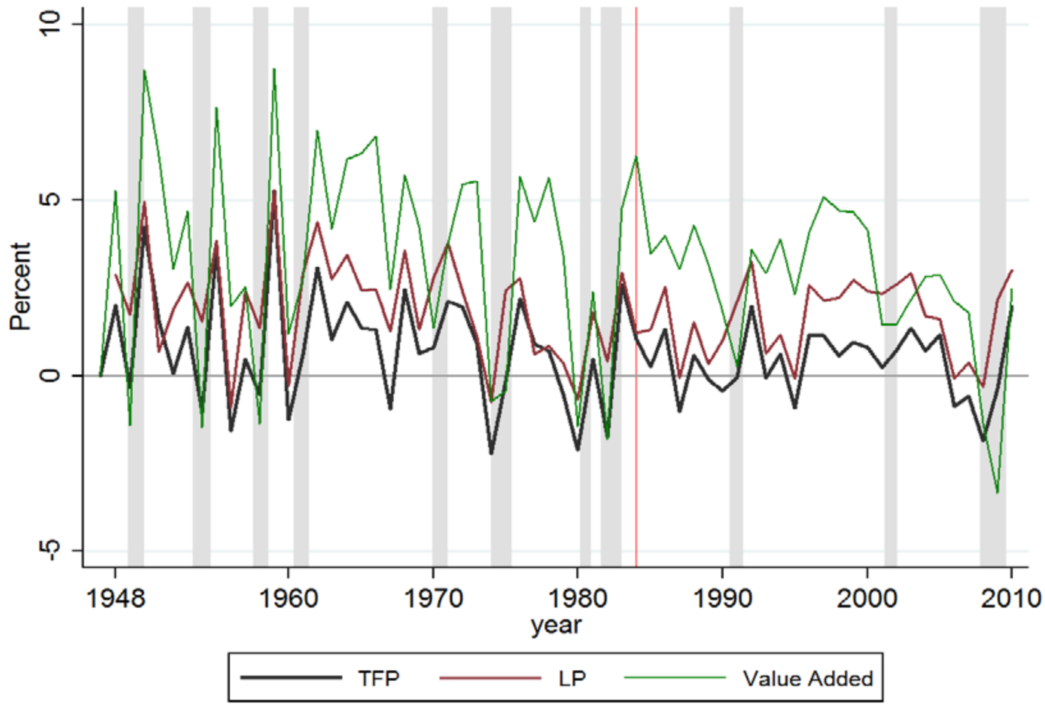
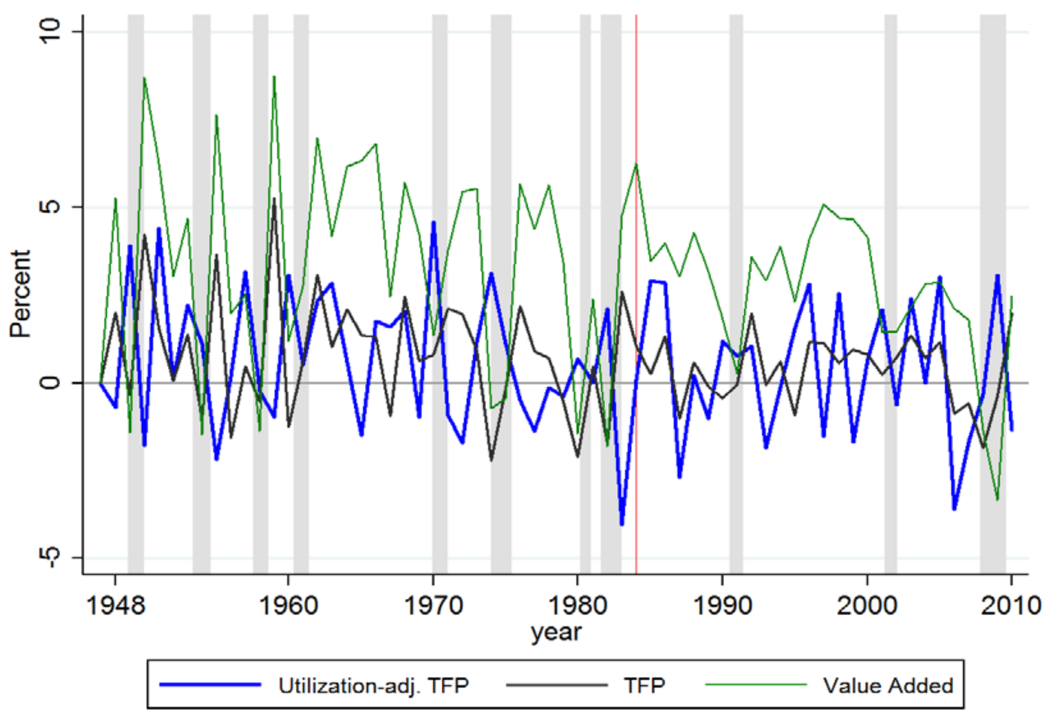


Figure 2b. Annual growth rate of TFP, utilization-adjusted TFP, and value added



Notes: These aggregate series are computed as described in Sections 3.1 and 3.2. The light grey areas mark recessions and the thin vertical red line marks 1984.

Figure 3a. Change in correlation between LP and primary input growth: FD- versus HP-filtered

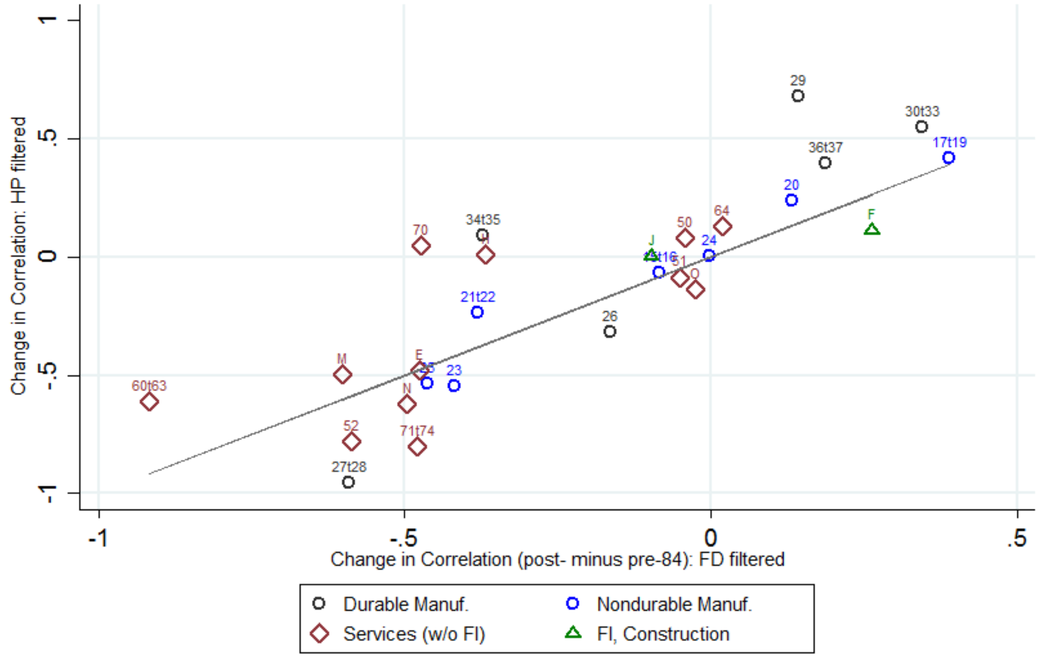
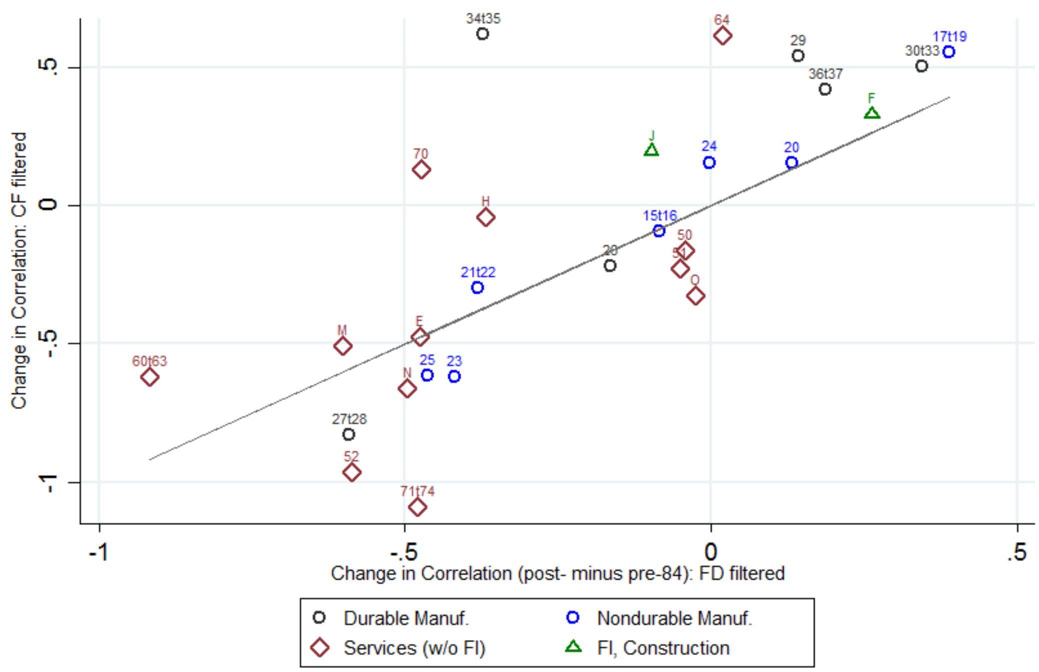
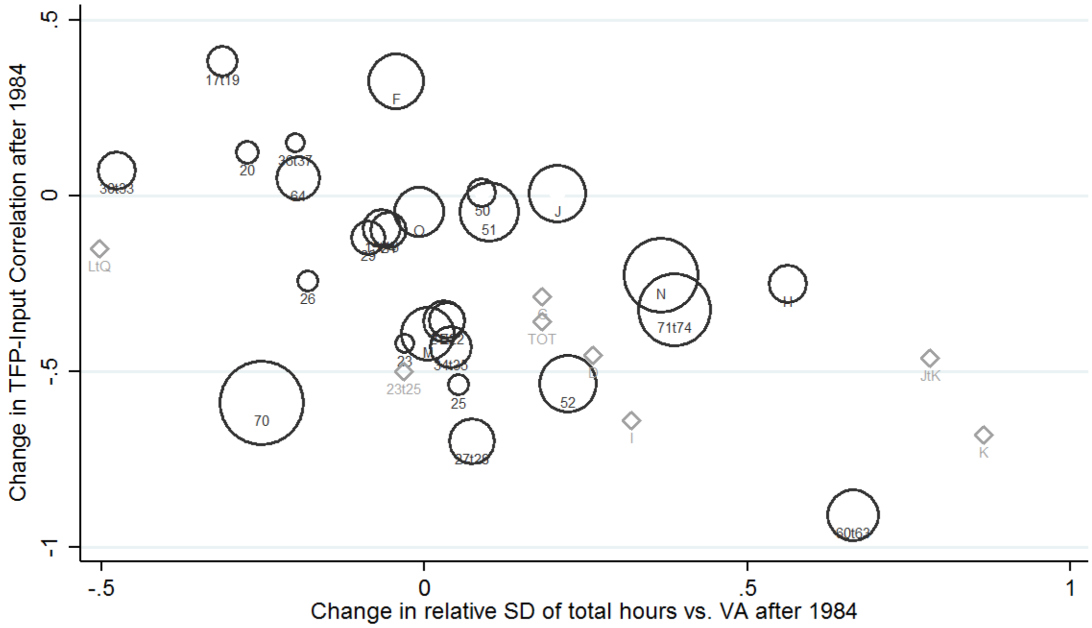


Figure 3b. Change in correlation between LP and primary input growth: FD- versus CF-filtered



Notes: These charts depict changes in the correlation between LP and input growth by industry based on different filters. HP: Hodrick-Prescott filter with the standard parameter for annual data; CF: Christiano-Fitzgerald filter, a form of bandpass filter with band 2 to 8 years; FD: first-difference, equivalent to annual growth rate. A 45-degree line is added to facilitate comparison.

Figure 4. Cross-industry pattern of change in TFP's correlation with primary input growth versus volatility ratio between total hours and VA after 1984
(slope coefficient estimate [heteroscedasticity robust standard error]: -0.620 [0.209])

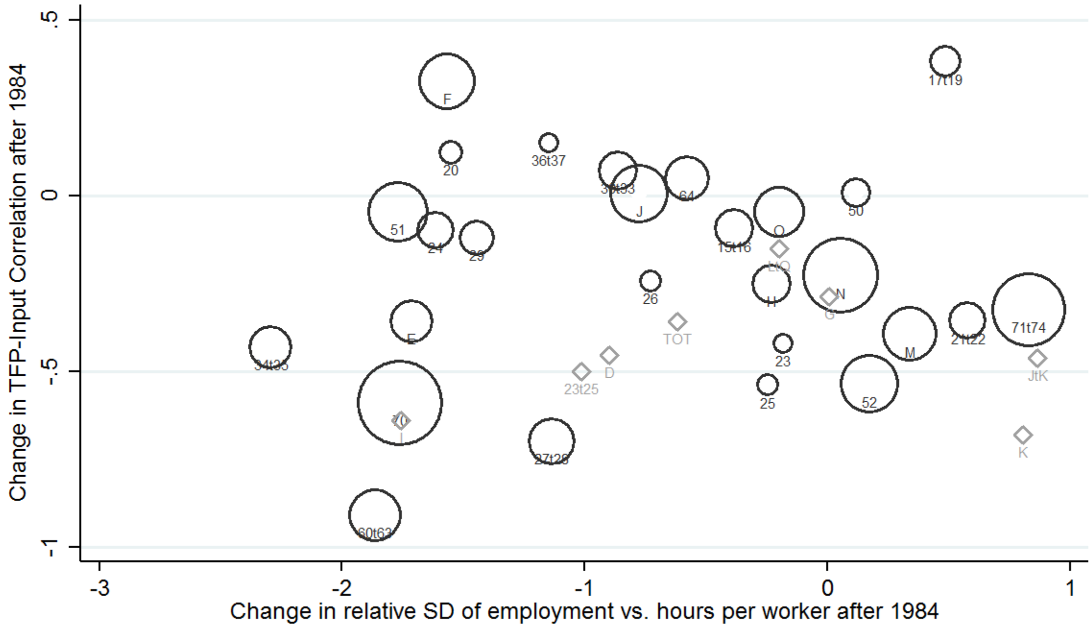


Notes: The black circles depict individual industries, while the light grey diamonds depict sectors and the total economy in the Jorgenson et al. dataset. Size of the circle proportional to an industry's time-series average VA share.

Figure 5. Cross-industry pattern of change in TFP's correlation with primary input growth versus volatility ratio between employment and VA after 1984
(slope coefficient estimate [heteroscedasticity robust standard error]: -0.759 [0.293])

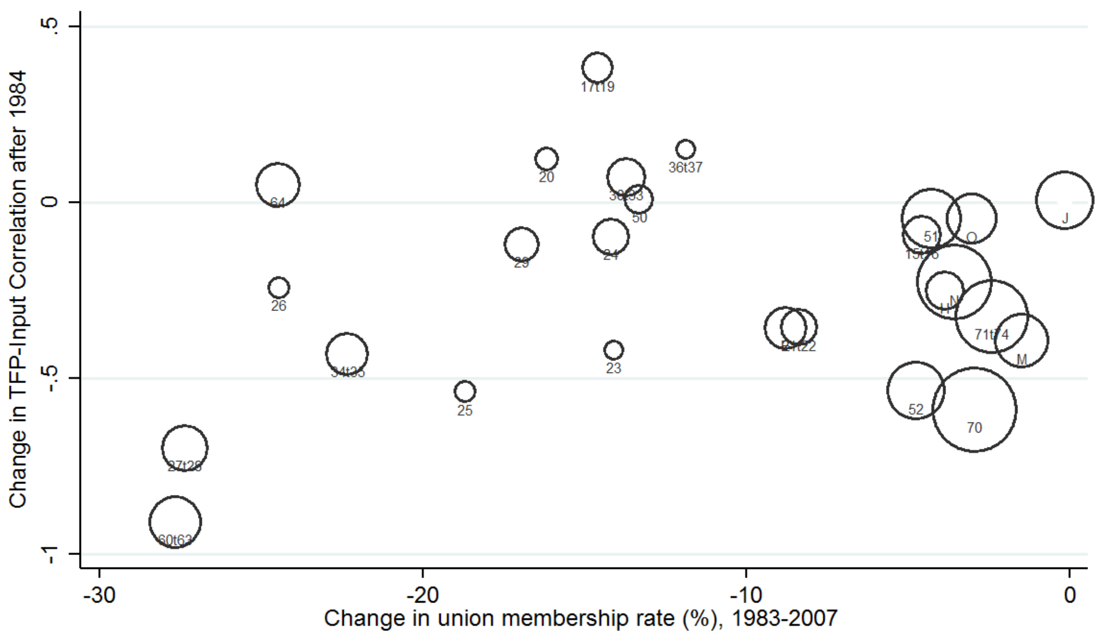
Notes: The black circles depict individual industries, while the light grey diamonds depict sectors and the total economy in the Jorgenson et al. dataset. Size of the circle proportional to an industry's time-series average VA share.

Figure 6. Cross-industry pattern of change in TFP's correlation with primary input growth versus volatility ratio between employment and average hours per worker after 1984
(slope coefficient estimate [heteroscedasticity robust standard error]: 0.026 [0.075])



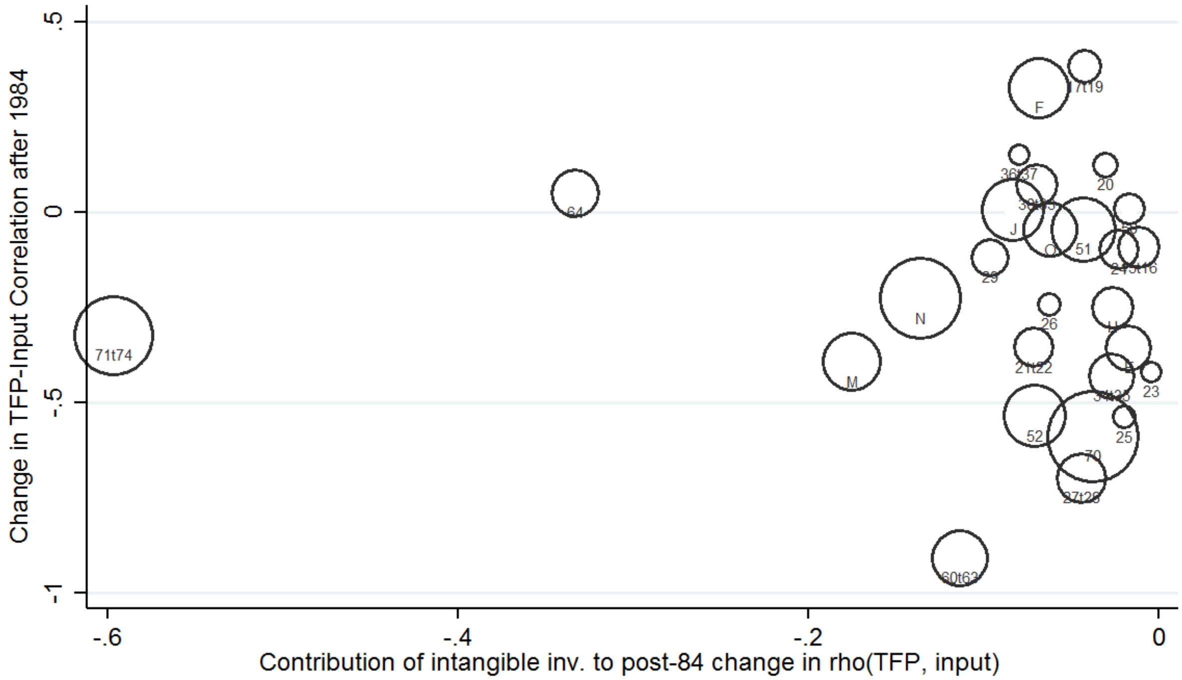
Notes: The black circles depict individual industries, while the light grey diamonds depict sectors and the total economy in the Jorgenson et al. dataset. Size of the circle proportional to an industry's time-series average VA share.

Figure 7. Cross-industry pattern of change in TFP's correlation with primary inputs after 1984 versus change in union membership rate since 1983
(slope coefficient estimate [heteroscedasticity robust standard error] if restricting to industries with a decline in union membership rate of more than 10 percentage points : 0.045 [0.014])



Notes: The black circles depict individual industries, while the light grey diamonds depict sectors and the total economy in the Jorgenson et al. dataset. Size of the circle proportional to an industry's time-series average VA share.

Figure 8. Cross-industry pattern of change in TFP's correlation with primary inputs after 1984 versus the cyclicality of ICT investment



Notes: The black circles depict individual industries, while the light grey diamonds depict sectors and the total economy in the Jorgenson et al. dataset. Size of the circle proportional to an industry's time-series average VA share.

Table 1. Gross output production function parameter estimates: with CRS constraint

		Manufacturing		
RHS	Construction	Nondurable	Durable	Nonmanufacturing
Detrended hours	1.971	5.248*	1.338***	1.255*
	[2.274]	[2.373]	[0.309]	[0.691]
1973 dummy	-1.360	-0.195	0.447	-0.294
	[1.782]	[0.276]	[0.867]	[0.250]
Observations	58	406	348	696
# of industries	1	7	6	12
R-squared	-1.453	-1.750	0.079	-0.354
Adjusted R^2	-1.501	-1.812	0.058	-0.382

Notes: The estimation sample is 1950 to 2007. Industry-specific intercepts are omitted. Coefficients estimated using LIML with IVs consisting of real oil price shock, monetary policy shock, and real federal defense spending. The coefficient on composite inputs dx is constrained to 1. Regressions include industry fixed effects. Standard errors clustered by industry in brackets.

The notation for coefficient significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2. Gross output production function parameter estimates: without CRS constraint

		Manufacturing		
RHS	Construction	Nondurable	Durable	Nonmanufacturing
Composite inputs	1.063***	0.559	1.156***	0.720*
	[0.210]	[0.347]	[0.118]	[0.360]
Detrended hours	2.508	5.312***	0.871**	1.590*
	[3.135]	[1.297]	[0.272]	[0.860]
1973 dummy	-0.012	-1.332	0.809	-0.496*
	[0.010]	[0.843]	[0.775]	[0.264]
Observations	58	406	348	696
# of industries	1	7	6	12
R-squared	0.704	0.147	0.856	0.181
Adjusted R^2	0.666	0.125	0.853	0.163

Notes: The estimation sample is 1950 to 2007. Industry-specific intercepts are omitted. Estimated using LIML with IVs consisting of real oil price shock, monetary policy shock, and real federal defense spending. The coefficient on composite inputs dx is unconstrained. Regressions include industry fixed effects. Standard errors clustered by industry in brackets.

The notation for coefficient significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3a. Cyclical correlation between labor productivity and output (VA): 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.350	0.428	0.042	-0.386
CF	0.399	0.430	0.294	-0.136
HP	0.316	0.420	-0.092	-0.512
First Difference	0.561	0.64	0.168	-0.472

Table 3b. Cyclical correlation between labor productivity and primary inputs: 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	-0.185	-0.089	-0.475	-0.386
CF	-0.154	-0.125	-0.246	-0.121
HP	-0.228	-0.101	-0.584	-0.483
First Difference	0.065	0.206	-0.375	-0.581

Note: Bandpass filter with frequency band 2–8 years. HP: Hodrick-Prescott filter with $\lambda = 6.25$.
CF: Christiano-Fitzgerald (2003) filter, with frequency band 2–8 years.

Table 4a. Cyclical correlation between TFP and output (VA): 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.763	0.810	0.488	-0.322
CF	0.793	0.818	0.684	-0.134
HP	0.746	0.805	0.402	-0.403
First Difference	0.826	0.874	0.482	-0.392

Table 4b. Cyclical correlation between TFP and primary inputs: 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.276	0.363	-0.087	-0.450
CF	0.315	0.353	0.182	-0.171
HP	0.246	0.356	-0.175	-0.531
First Difference	0.376	0.497	-0.114	-0.611

Note: Bandpass filter with frequency band 2–8 years. HP: Hodrick-Prescott filter with $\lambda = 6.25$.
CF: Christiano-Fitzgerald (2003) filter, with frequency band 2–8 years.

Table 5a. Cyclical correlation between utilization-adjusted TFP and output (VA): 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	-0.402	-0.470	-0.302	0.168
CF	-0.492	-0.578	-0.341	0.237
HP	-0.406	-0.476	-0.301	0.175
First Difference	-0.224	-0.331	0.027	0.358

Table 5b. Cyclical correlation between utilization-adjusted TFP and primary inputs: 1950–2007

Filter	1950 - 2007	1950 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	-0.322	-0.236	-0.512	-0.276
CF	-0.404	-0.307	-0.606	-0.299
HP	-0.333	-0.249	-0.504	-0.255
First Difference	-0.207	-0.182	-0.272	-0.090

Note: Bandpass filter with frequency band 2–8 years. HP: Hodrick-Prescott filter with $\lambda = 6.25$.
CF: Christiano-Fitzgerald (2003) filter, with frequency band 2–8 years.

Table 6. Changes in LP-VA correlation $\rho(\mathrm{d}a, \mathrm{d}v)$ and LP-input correlation $\rho(\mathrm{d}a, \mathrm{d}x^V)$ across private industries based on different filters

Panel A. Cross-industry statistics of post-1984 change in $\rho(\mathrm{d}a, \mathrm{d}v)$ based on different filters

	Mean	S.D.	Corr. with FD filter	Corr. with CF filter
FD filter	-0.006	0.194	1	
CF filter	0.015	0.23	0.85	1
HP filter	-0.003	0.237	0.87	0.97

Panel B. Cross-industry statistics of post-1984 change in $\rho(\mathrm{d}a, \mathrm{d}x^V)$ based on different filters

	Mean	S.D.	Corr. with FD filter	Corr. with CF filter
FD filter	-0.208	0.336	1	
CF filter	-0.131	0.509	0.76	1
HP filter	-0.144	0.43	0.84	0.93

Note: The above two tables report the unweighted mean, standard deviation, and simple correlations across 27 private industries in terms of the post-1984 change in $\rho(\mathrm{d}a, \mathrm{d}v)$ and $\rho(\mathrm{d}a, \mathrm{d}x^V)$ when data are detrended using different filters, to summarize how robust the cross-industry patterns are to the filtering method. For the corresponding cross-industry scatterplots, see Figures 2a and 2b.

Table 7. Change in cyclicality of LP versus TFP using first-differenced data

	Mean	S.D.	Corr. with LP-VA	Corr. with LP-Input
TFP-VA **$\Delta\rho(\mathrm{d}t, \mathrm{d}v)$**	-0.024	0.131	0.94	--
TFP-Input **$\Delta\rho(\mathrm{d}t, \mathrm{d}x^{V})$**	-0.207	0.309	--	0.93

Note: This table compares the unweighted mean, standard deviation, and simple correlations across 27 industries between TFP and LP's cyclicality with respect to VA and primary inputs.

Table 8. Within- versus cross-industry decomposition of aggregate TFP-input correlation

	Aggregate Correlation	Within Industry	Cross Industry
Pre-1984	0.497	0.016	0.481
Post-1984	-0.114	-0.078	-0.036
Change	-0.611	-0.094	-0.517
Contribution to change in aggregate correlation (normalized to a per-pair basis)			
Pre-84 contribution (in basis points)		0.058	0.069
Post-84 contribution (in basis points)		-0.291	-0.005
Contribution to aggregate change (in bp)		-0.348	-0.074

Note: This table presents the decomposition of the aggregate TFP-input correlation and its change after 1984 into weighted average within- versus cross-industry components. The contributions are normalized to an equal-weighted per industry pair basis and scaled to basis points to facilitate comparison.

Table 9. Decomposition of TFP-input correlation $\rho(\mathrm{d}t, \mathrm{d}x^V)$, and its change after 1984

Panel A. TFP-input correlation $\rho(\mathrm{d}t, \mathrm{d}x^V)$, its change after 1984, and the contribution of utilization versus technology

	$\rho(\mathrm{d}t, \mathrm{d}x^V)$			Contribution of du to $\rho(\mathrm{d}t, \mathrm{d}x^V)$			Contribution of dz to $\rho(\mathrm{d}t, \mathrm{d}x^V)$		
	Before 1984	**After 1984**	**Change**	**Before 1984**	**After 1984**	**Change**	**Before 1984**	**After 1984**	**Change**
Aggregate nonfarm business industries	**0.50**	**-0.11**	**-0.61**	**0.70**	**0.60**	**-0.10**	**-0.20**	**-0.65**	**-0.45**
Construction	-0.26	0.07	0.32	0.65	1.08	0.43	-0.91	-0.99	-0.08
Manuf., Nondurable	0.37	-0.11	-0.48	1.70	1.43	-0.27	-1.30	-1.55	-0.24
Manufacturing, Durable	0.46	0.21	-0.25	0.47	0.40	-0.06	0.05	-0.10	-0.15
Services (excluding FI)	0.35	-0.31	-0.66	0.12	0.32	0.19	0.19	-0.61	-0.80

Panel B. Correlation of utilization (du) and technology (dz) with input growth (dx^V)

	$\rho(\mathrm{d}u, \mathrm{d}x^V)$			$\rho(\mathrm{d}z, \mathrm{d}x^V)$		
	Before 1984	**After 1984**	**Change**	**Before 1984**	**After 1984**	**Change**
Aggregate nonfarm business industries	**0.40**	**0.29**	**-0.11**	**-0.18**	**-0.27**	**-0.09**
Construction	0.65	0.57	-0.09	-0.56	-0.45	0.11
Manuf., Nondurable	0.54	0.43	-0.11	-0.46	-0.44	0.02
Manufacturing, Durable	0.49	0.31	-0.18	0.07	-0.07	-0.14
Services (excluding FI)	0.25	0.33	0.08	0.18	-0.39	-0.57

Panel B. Volatility of TFP (dt), utilization (du) and technology (dz)

	$\sigma(\mathrm{d}t)$			$\sigma(\mathrm{d}u)$			$\sigma(\mathrm{d}z)$		
	Before 1984	**After 1984**	**Post/Pre-'84 Ratio**	**Before 1984**	**After 1984**	**Post/Pre-'84 Ratio**	**Before 1984**	**After 1984**	**Post/Pre-'84 Ratio**
Aggregate nonfarm business industries	**1.78**	**0.80**	**0.45**	**3.09**	**1.67**	**0.54**	**1.97**	**1.93**	**0.98**
Construction	4.30	2.83	0.66	4.25	5.38	1.27	6.98	6.17	0.89
Manuf., Nondurable	5.43	3.66	0.68	17.22	12.25	0.71	15.35	12.98	0.85
Manufacturing, Durable	4.53	2.82	0.62	4.31	3.62	0.84	3.43	3.78	1.10
Services (excluding FI)	1.60	0.88	0.55	0.80	0.84	1.05	1.69	1.38	0.82

Notes: The three panels of this table present the decomposition of $\rho(\mathrm{d}t, \mathrm{d}x^V)$ according to equation (14) in the text for both aggregate private industries and the four sectors.

Table 10. Responses of output and inputs to technology shocks: before 1984 and the change after 1984
(based on the CRS production function parameters, reported in Table 1)

RHS	(1) VA	(2) Inputs	(3) Total hours	(4) Employment	(5) Detrended hours	(6) Utilization	(7) TFP (VA-basis)	(8) LP	(9) Implicit VA deflator
dz	-0.426**	-0.198	-0.390**	-0.216	-0.180***	-1.215***	-0.227*	-0.0359	-0.133
	[0.206]	[0.121]	[0.155]	[0.141]	[0.0288]	[0.122]	[0.119]	[0.108]	[0.200]
dz*D_{post84}	0.516*	0.0289	0.132	0.138	0.00268	0.498***	0.487***	0.384***	-0.0300
	[0.264]	[0.186]	[0.236]	[0.209]	[0.0369]	[0.144]	[0.144]	[0.148]	[0.225]
dz(-1)	-0.143	-0.308**	-0.583***	-0.561***	-0.0309	0.169	0.166	0.441***	-0.605***
	[0.233]	[0.136]	[0.175]	[0.159]	[0.0325]	[0.138]	[0.135]	[0.122]	[0.226]
dz(-1)*D_{post84}	0.177	0.177	0.387	0.382*	0.0138	-0.0204	-0.000355	-0.210	0.383
	[0.291]	[0.202]	[0.257]	[0.228]	[0.0407]	[0.160]	[0.160]	[0.162]	[0.251]
dz(-2)	0.859***	0.283**	0.396**	0.281*	0.113***	0.540***	0.577***	0.463***	-0.692***
	[0.231]	[0.135]	[0.173]	[0.158]	[0.0322]	[0.137]	[0.134]	[0.121]	[0.224]
dz(-2)*D_{post84}	-0.589**	-0.223	-0.328	-0.265	-0.0637	-0.306*	-0.367**	-0.261	0.443*
	[0.299]	[0.211]	[0.267]	[0.237]	[0.0417]	[0.162]	[0.163]	[0.168]	[0.253]
dz(-3)	0.480**	0.348***	0.386**	0.334**	0.0615*	0.159	0.133	0.0936	-0.698***
	[0.228]	[0.133]	[0.171]	[0.156]	[0.0318]	[0.135]	[0.132]	[0.119]	[0.221]
dz(-3)*D_{post84}	-0.307	-0.249	-0.260	-0.235	-0.0282	-0.0672	-0.0592	-0.0465	0.612**
	[0.299]	[0.212]	[0.269]	[0.239]	[0.0418]	[0.162]	[0.162]	[0.168]	[0.251]
dz(-4)	0.357*	0.281**	0.288*	0.299**	0.00762	0.0701	0.0770	0.0685	-0.344*
	[0.215]	[0.126]	[0.161]	[0.147]	[0.0300]	[0.127]	[0.125]	[0.113]	[0.209]
dz(-4)*D_{post84}	-0.193	-0.244	-0.202	-0.241	0.0302	0.0688	0.0493	0.00826	0.293
	[0.276]	[0.194]	[0.247]	[0.219]	[0.0386]	[0.150]	[0.151]	[0.155]	[0.235]
D_{post84}	0.297	0.356	0.143	-0.218	0.0144	-0.0238	-0.0532	0.154	-3.287***
	[0.765]	[0.508]	[0.646]	[0.578]	[0.107]	[0.430]	[0.427]	[0.419]	[0.684]
Constant	2.554***	2.402***	1.468***	1.936***	0.0143	0.0534	0.147	1.086***	6.315***
	[0.661]	[0.387]	[0.496]	[0.452]	[0.0923]	[0.392]	[0.383]	[0.347]	[0.642]
σ*D_{post84}	-0.903***	-0.190	-0.266	-0.296	-0.125***	-0.703***	-0.640***	-0.363**	-1.321***
	[0.323]	[0.221]	[0.280]	[0.250]	[0.0452]	[0.179]	[0.178]	[0.179]	[0.283]
σ(resid.)	2.168***	1.270***	1.627***	1.481***	0.303***	1.285***	1.257***	1.137***	2.104***
	[0.267]	[0.156]	[0.200]	[0.182]	[0.0372]	[0.158]	[0.155]	[0.140]	[0.259]
Observations	57	57	57	57	57	57	57	57	57
chi2	27.96	27.63	38.95	33.52	167.3	303.4	42.56	41.65	39.71

Notes: Heteroscedasticity robust standard errors in brackets. The notation for coefficient significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Responses of utilization to technology shocks before 1984 and the change afterward: summary statistics of industry-level regressions

RHS	Mean	S.D.	Median	Min.	Max.	# Signif. Positive	# Signif. Negative
dz	-0.346	0.307	-0.288	-0.938	0.0606	1	17
dz*D_{post84}	-0.112	0.188	-0.118	-0.505	0.259	3	8
dz(-1)	0.0553	0.123	0.0604	-0.143	0.382	7	2
dz(-1)*D_{post84}	0.00195	0.155	-0.00828	-0.358	0.279	1	1
dz(-2)	0.0845	0.104	0.0727	-0.203	0.294	6	0
dz(-2)*D_{post84}	-0.0258	0.187	0.0128	-0.511	0.296	3	2
dz(-3)	0.0409	0.111	0.0495	-0.166	0.341	4	0
dz(-3)*D_{post84}	-0.0245	0.131	-0.00643	-0.402	0.237	1	2
dz(-4)	-0.0192	0.0677	-0.0114	-0.192	0.0998	1	1
dz(-4)*D_{post84}	0.0508	0.116	0.0701	-0.191	0.243	2	0
D_{post84}	-0.0899	0.733	-0.0528	-2.244	1.428		
Constant	0.119	0.438	0.00238	-0.447	1.561		
σ*D_{post84}	-0.984	2.675	-0.365	-11.61	2.224	5	7
σ(resid.)	4.134	5.185	3.126	0.734	26.80		

Notes: This table reports summary statistics of the coefficient estimates from 27 industry-level regressions with the same specification as that in column (6) of Table 10 above.

Table 12. Persistence of technology shocks (dz): before 1984 and change afterward

RHS	1950-2007	1948-2010
dz(-1)	0.108	0.104
	[0.194]	[0.175]
dz(-1)*D_{post84}	0.364**	0.350**
	[0.152]	[0.154]
D_{post73}	-0.702***	-0.722***
	[0.171]	[0.157]
Constant	0.911***	0.928***
	[0.212]	[0.191]
ε(-1)	-1.000	-1.000
	[378.6]	[165.6]
σ(ε)	1.540	1.528
	[291.5]	[126.5]
Observations	58	63
Chi-squared	184.6	249.9

Note: The dependent variable is dz for both regressions, which differ only in their sample periods, as specified in the header row. The notation for coefficient significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 13. Decomposition of aggregate TFP into aggregate technology and allocation
(with returns to scale constrained to 1)

	Correlation with input growth			Contribution
	Before 1984	**After 1984**	**Change**	**(%)**
Aggregate TFP	0.497	-0.114	-0.611	100.0
Aggregate Technology	-0.182	-0.272	-0.091	74.2
(Average markup -1)*aggregate input	--	--	--	--
Utilization scaled by markup	0.401	0.288	-0.113	16.0
All reallocation	0.001	-0.281	-0.282	9.9
Intermediate input reallocation	--	--	--	--
Other reallocation	0.001	-0.281	-0.282	9.9

	Correlation with VA growth			Contribution
	Before 1984	**After 1984**	**Change**	**(%)**
Aggregate TFP	0.874	0.482	-0.392	100.0
Aggregate Technology	-0.331	0.027	0.358	-110.1
(Average markup -1)*aggregate input	--	--	--	--
Utilization scaled by markup	0.706	0.219	-0.487	196.9
All reallocation	0.098	-0.186	-0.284	13.1
Intermediate input reallocation	--	--	--	--
Other reallocation	0.098	-0.186	-0.284	13.1

Note: This table decomposes the change in TFP's cyclicality into the contribution from technology versus those from input utilization and allocation. The top panel decomposes TFP's correlation with inputs, and the bottom panel TFP's correlation with output (VA).

Table 14. Decomposition of aggregate TFP into aggregate technology and allocation
(with unconstrained returns to scale estimate)

	Correlation with input growth			Contribution
	Before 1984	**After 1984**	**Change**	**(%)**
Aggregate TFP	0.497	-0.114	-0.611	100.0
Aggregate Technology	-0.028	-0.069	-0.041	22.9
(Average markup -1)*aggregate input	-0.9990	-0.9988	0.0002	24.4
Utilization scaled by markup	0.396	0.300	-0.097	4.8
All reallocation	0.185	-0.466	-0.651	47.9
Intermediate input reallocation	-0.250	-0.587	-0.337	34.4
Other reallocation	0.710	0.266	-0.444	13.5

	Correlation with VA growth			Contribution
	Before 1984	**After 1984**	**Change**	**(%)**
Aggregate TFP	0.874	0.482	-0.392	100.0
Aggregate Technology	-0.163	0.224	0.387	-179.3
(Average markup -1)*aggregate input	-0.861	-0.812	0.049	28.5
Utilization scaled by markup	0.700	0.198	-0.502	194.9
All reallocation	0.067	-0.387	-0.454	56.0
Intermediate input reallocation	-0.336	-0.547	-0.212	42.5
Other reallocation	0.666	0.406	-0.260	13.5

Note: This table decomposes the change in TFP's cyclicality into the contribution from technology versus those from input utilization and allocation. The top panel decomposes TFP's correlation with inputs, and the bottom panel TFP's correlation with output (VA).

Appendix I. Relationship between Aggregate Productivity and Technology

This appendix adapts Basu and Fernald's (BF 2002) derivation of the relationship between aggregate productivity and aggregate technology to a formulation that uses Domar weights to convert gross-output-based measures to value-added-based measures. It also extends the formulas to include the utilization adjustment, as in Basu, Fernald, and Kimball (2006). Start with the basic relationship derived in Hall (1990) that, as long as firms minimize cost, gross output growth, ($\mathrm{d}y$), equals revenue-share-weighted composite input growth scaled by the markup, plus gross-output-augmenting technology change, $\mathrm{d}z$. Inputs include both measured components ($\mathrm{d}x$, such as labor and capital) and unmeasured elements ($\mathrm{d}u$, such as utilization rate). For any industry i, this relationship can be written as:[39]

$$\mathrm{d}y_{it} = \mu_i\left(\mathrm{d}x_{it} + \mathrm{d}u_{it}\right) + \mathrm{d}z_{it} = \mu_i(s_{Li}\mathrm{d}l_{it} + s_{Ki}\mathrm{d}k_{it} + s_{Mi}\mathrm{d}m_{it} + \mathrm{d}u_{it}) + \mathrm{d}z_{it}\,. \qquad (17)$$

$\mathrm{d}l$, $\mathrm{d}k$, and $\mathrm{d}m$ denote, respectively, the growth rates (defined as log difference) of labor (L), capital (K), and all intermediate inputs (M, which can be further disaggregated into materials, energy, and purchased services). $\mathrm{d}u$ denotes the composite utilization term, including both labor effort and capital utilization.[40] Cost minimization implies that this term can be approximated, to a first order, by the observed intensive margin of average (weekly) hours, as shown in Basu and Kimball (1997). s_{Li}, s_{Ki}, and s_{Mi} are the revenue shares of L, K, and M, respectively. These shares sum to less than one if there is pure profit. μ denotes the markup on gross output. μ and returns to scale, γ, are related through the relationship $\gamma = \mu(1 - s_\pi)$, where s_π is the revenue share of economic profit. Since there is adequate evidence that s_π is negligible in aggregate data, especially on average over time, we by and large use μ and γ interchangeably.[41]

Treating $\mathrm{d}y$ as a Divisia index of $\mathrm{d}v$ and $\mathrm{d}m$ as in Basu and Fernald (2002), we can show that equation (17) then implies:[42]

$$\mathrm{d}v := \frac{\mathrm{d}y - s_{Mi}\mathrm{d}m}{1 - s_{Mi}} = \frac{\mu_i\left(\mathrm{d}x + \mathrm{d}u\right) + \mathrm{d}z - s_{Mi}\mathrm{d}m}{1 - s_{Mi}} = \mu_i\left(dx^V + du^V\right) + \left(\mu_i - 1\right)\frac{s_{Mi}}{1 - s_{Mi}}\mathrm{d}m + \mathrm{d}z^V\,, \qquad (18)$$

The terms with a V superscript, meant to denote that these variables are defined or scaled to be consistent with value added, are defined as follows:

[39] Here, the unit for the technology change is chosen to yield a unitary elasticity of gross output with regard to Z. To be more precise, this equation holds at the individual-firm level. To apply it to an industry implicitly assumes that there exists a representative firm for each industry, so there are no aggregation-related issues at the industry level.
[40] See Basu and Kimball (1997) for detailed derivations and a more detailed discussion of how this formulation can capture, to a first-order, time-varying utilization of capital in the form of either physical depreciation or, likely more relevant for most industries, a wage premium paid to labor because of a longer work week.
[41] There may still be interesting cyclical variations in s_π, but we subsume them into variations in μ.
[42] For clarity of exposition, subscripts *it* for growth rates are omitted.

$$\mathrm{d}x^V = \frac{s_{Li}}{1-s_{Mi}}\mathrm{d}l + \frac{s_{Ki}}{1-s_{Mi}}\mathrm{d}k \equiv s_{Li}^V \mathrm{d}l + s_{Ki}^V \mathrm{d}k\,, \tag{19}$$

$$\mathrm{d}u^V = \mathrm{d}u \big/ \left(1-s_{Mi}\right), \tag{20}$$

$$\mathrm{d}z^V = \mathrm{d}z \big/ \left(1-s_{Mi}\right). \tag{21}$$

$\mathrm{d}x^V$ is the growth rate of primary inputs, $\mathrm{d}u^V$ is the VA-based utilization, while $\mathrm{d}z^V$ is the growth rate of VA-augmenting technology. s_L^V and s_K^V are the VA shares of labor and capital, respectively. Obviously, with perfect competition, equation (18) reduces to the more familiar relationship of $\mathrm{d}v = \mathrm{d}x^V + \mathrm{d}z^V$.

By comparison, BF (2002) scale up the growth rates using $\left(1-\mu s_{Mi}\right)$ instead of $\left(1-s_{Mi}\right)$. The former correctly accounts for intermediate inputs' contribution to gross output even when there are increasing returns or imperfect competition, in which case their share in revenue (s_M) should be multiplied by the gross-output markup (μ). Accordingly, they define the markup on value added as $\mu^V = \mu\left(1-s_M\right)/\left(1-\mu s_M\right)$, which exceeds the markup on gross output when $\mu > 1$. In contrast, using $\left(1-s_{Mi}\right)$ assigns any extra contribution beyond intermediate inputs' share in revenue to value added. Even though the former is preferred conceptually, it can introduce significant errors into the computation empirically because of estimation errors in μ. We therefore use $\left(1-s_{Mi}\right)$. Moreover, this is consistent with the Domar weighting for aggregation used widely in productivity studies.

Equation (18) then implies that the VA-base TFP, $\mathrm{d}t$, defined as $\mathrm{d}v$ - $\mathrm{d}x^V$, is as follows:

$$\mathrm{d}t_{it} = \left(\mu_i - 1\right)\mathrm{d}x_{it}^V + \mu_i \mathrm{d}u_{it}^V + \left(\mu_i - 1\right)\frac{s_{Mi}}{1-s_{Mi}}\mathrm{d}m_{it} + \mathrm{d}z_{it}^V = \left(\mu_i - 1\right)\frac{\mathrm{d}x_{it}}{1-s_{Mi}} + \mu_i \mathrm{d}u_{it}^V + \mathrm{d}z_{it}^V\,. \tag{22}$$

Obviously, with perfect competition, the first term after the second equal sign becomes zero, so $\mathrm{d}t$ equals $\mathrm{d}u^V + \mathrm{d}z^V$; that is, TFP still measures both true technology and utilization (on a VA scale), but there is no longer a contribution from inputs due to markup.

Here, we can derive the relationship between cyclicality measures based on TFP's correlation with output versus its correlation with inputs. In particular, we show that, in levels, the former, $\rho(\mathrm{d}t, \mathrm{d}v)$, always exceeds the latter, $\rho(\mathrm{d}t, \mathrm{d}x^V)$. Moreover, under certain conditions, the reduction in $\rho(\mathrm{d}t, \mathrm{d}x^V)$ exceeds the reduction over time in $\rho(\mathrm{d}t, \mathrm{d}v)$. To start, it is obvious that TFP's covariance with output exceeds that with inputs because $\mathrm{cov}(\mathrm{d}t, \mathrm{d}x^V) = \mathrm{cov}(\mathrm{d}t, \mathrm{d}v) - \mathrm{var}(\mathrm{d}t)$. It turns out that TFP's correlation with output always exceeds its correlation with input as well, and this can be derived using the definition $\mathrm{d}v = \mathrm{d}x^V + \mathrm{d}t$ and the implied inequality $\sigma(\mathrm{d}x^V) + \sigma(\mathrm{d}t) \geq \sigma(\mathrm{d}v)$, since $\rho(\mathrm{d}t, \mathrm{d}x^V) \leq 1$:

$$\rho(\mathrm{d}t,\mathrm{d}v)=\rho(\mathrm{d}t,\mathrm{d}x^V)\frac{\sigma(\mathrm{d}x^V)}{\sigma(\mathrm{d}v)}+\frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)}\geq\rho(\mathrm{d}t,\mathrm{d}x^V)\left[\frac{\sigma(\mathrm{d}x^V)+\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)}\right]\geq\rho(\mathrm{d}t,\mathrm{d}x^V)\,. \tag{23}$$

In terms of the relative change over time, any difference in terms of covariance must be due to changes in $\sigma(\mathrm{d}t)$. The relationship between the two correlations, however, is less clear cut, since

$$\Delta\rho(\mathrm{d}t,\mathrm{d}v)-\Delta\rho(\mathrm{d}t,\mathrm{d}x^V)\approx\Delta\rho(\mathrm{d}t,\mathrm{d}x^V)\left[\frac{\sigma_0(\mathrm{d}x^V)}{\sigma_0(\mathrm{d}v)}-1\right]+\rho_0(\mathrm{d}t,\mathrm{d}x^V)\Delta\left[\frac{\sigma(\mathrm{d}x^V)}{\sigma(\mathrm{d}v)}\right]+\Delta\left[\frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)}\right]. \tag{24}$$

The subscript 0 denotes the first (pre-1984) subperiod. If $\rho_0(\mathrm{d}t,\, \mathrm{d}x^V) > 0$ and $\Delta\rho(\mathrm{d}t,\, \mathrm{d}x^V) < 0$, we can derive that the net sign of the right-hand side is positive. The first term is positive because $\rho_0(\mathrm{d}t,\, \mathrm{d}v) > 0$ implies that $\sigma_0(\mathrm{d}v) > \sigma_0(\mathrm{d}x^V)$. The sum of the last two terms is greater than or equal to the following expression:

$$\rho_0(\mathrm{d}t,\mathrm{d}x^V)\left\{\Delta\left[\frac{\sigma(\mathrm{d}x^V)}{\sigma(\mathrm{d}v)}\right]+\Delta\left[\frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)}\right]\right\}\geq\rho_0(\mathrm{d}t,\mathrm{d}x^V)\frac{\Delta\sigma(\mathrm{d}x^V)+\Delta\sigma(\mathrm{d}t)-\Delta\sigma(\mathrm{d}v)}{\sigma_0(\mathrm{d}v)}\,.$$

$\Delta\rho(\mathrm{d}t,\, \mathrm{d}v) < 0$ implies that $\Delta\sigma(\mathrm{d}x^V) + \Delta\sigma(\mathrm{d}t) > \Delta\sigma(\mathrm{d}v)$. Therefore, all three terms on the right-hand side are positive. This means that as long as TFP and input start out positively correlated but become less so over time, the decline in TFP's correlation with input must exceed the decline in its correlation with output. As shown in the paper, this exactly describes the empirical situation at the aggregate level.

VA-based TFP growth at the economy level is defined analogously, as $\mathrm{d}v_t-\mathrm{d}x_t^V$. $\mathrm{d}v_t$ is aggregate value added growth, defined as $\mathrm{d}v_t=\sum_i w_i \mathrm{d}v_{it}$, where $w_i=P_{it}V_{it}\big/\sum_i P_{it}V_{it}$ is i's share in total nominal VA. $\mathrm{d}x_t^V$ is aggregate primary input growth, defined as $\mathrm{d}x_t^V=s_L^V\mathrm{d}l_t+s_K^V\mathrm{d}k_t$, where s_L^V and s_K^V are the respective shares of labor and capital income in aggregate VA, while $\mathrm{d}l$ and $\mathrm{d}k$ are the growth rates of aggregate labor and capital input, respectively. BF (2002) show that, if we allow identical inputs to command different prices across firms or industries because of frictions such as adjustment costs, then $\mathrm{d}x_t^V$ differs from VA-weighted-average of $\mathrm{d}x_{it}^V$ as follows:

$$\mathrm{d}x_t^V=\sum_i w_i\mathrm{d}x_{it}^V-R_{L,t}-R_{K,t}\,. \tag{25}$$

R_L and R_K are two terms that stem from reallocating labor and capital (of any given type) across firms that compensate them at different rates.[43] Intuitively, if a given input is reallocated from a lower- to a higher-paying use, then aggregate input does not rise as fast as VA-weighted-average firm inputs because the factor's private marginal cost exceeds its social marginal cost (by more), and thus its

[43] See BF (2002, p. 978) for detailed expressions. Also note that their derivation is based on the simplifying assumption of a single type of labor as well as capital, although the principle remains the same with multiple types of labor and capital.

contribution to $\mathrm{d}x_{it}^{V}$ overstates its contribution to $\mathrm{d}x_{t}^{V}$. Note that, to the extent observed factor prices deviate from their shadow values at a point in time, these deviations are also included in R_L and R_K.

Plugging (22) into the definition of aggregate TFP, we derive the following expressions:

$$\mathrm{d}t_t = \mathrm{d}v_t - \mathrm{d}x_t^V = \sum_i w_i \mathrm{d}t_{it} + R_{L,t} + R_{K,t} = \left[\left(\bar{\mu}-1\right)\mathrm{d}x_t^V + \mathrm{d}\bar{u}_t^V + R_{M,t}\right] + R_{\mu,t} + \bar{\mu}\left(R_{L,t} + R_{K,t}\right) + \mathrm{d}z_t^V, \quad (26)$$

where

$$\bar{\mu} = \sum_i w_i \mu_i,$$

$$\mathrm{d}\bar{u}_t^V = \sum_i w_i \mu_i \mathrm{d}u_{it}^V,$$

$$R_{M,t} = \sum_i w_i \left(\mu_i - 1\right)\frac{s_{Mi}}{1-s_{Mi}}\mathrm{d}m_{it},$$

$$R_{\mu,t} = \sum_i w_i \left(\mu_i - \bar{\mu}\right)\mathrm{d}x_{it}^V,$$

$$\mathrm{d}z_t^V = \sum_i w_i \mathrm{d}z_{it}^V.$$

$\bar{\mu}$ is the weighted average markup. $\mathrm{d}\bar{u}_t^V$ denotes the first-order contribution from unmeasured inputs, and R_M the contribution from intermediate inputs when there are increasing returns or imperfect competition. R_μ stems from reallocation across firms with different markups. $\mathrm{d}z_t^V$ is the aggregate VA-augmenting technology. We group the first three terms together because they can in principle be computed using data and production-function parameter estimates, although they then inherit the estimation errors. Alternatively, we can group R_M with the other reallocation terms to form a composite reallocation term, that is:

$$\mathbf{R} = R_{M,t} + R_{\mu,t} + \bar{\mu}\left(R_{L,t} + R_{K,t}\right). \quad (27)$$

Clearly, if $\mu_i = 1$ for all i's, corresponding to no markup, only $R_{L,t} + R_{K,t}$ will remain, while the reallocation effect due to intermediate input and different markups will disappear. If, in addition to perfect competition, we also have identical factor prices across firms, all the reallocation terms disappear and $\mathrm{d}t_t = \mathrm{d}\bar{u}_t^V + \mathrm{d}z_t^V$. That is, aggregate TFP still differs from aggregate technology by the utilization term, which would disappear only if there were no internal adjustment costs.

In summary, (26) shows that aggregate TFP growth includes not only technology growth but also contributions from unmeasured inputs and the reallocation of resources across firms. It should be informative to examine how much of the declining procyclicality of aggregate TFP (and LP) is attributable to each of these terms.

Appendix II. Change in LP's Cyclicality with Both Input and Output Measurement Errors

This appendix derives expressions for the change in LP's cyclicality when there exist measurement errors in both inputs and output. For brevity of exposition, and because this is the input emphasized in Gali and van Rens's (2010) proposed explanations for the change in measured LP, we focus only on labor input. With this simplification, LP and TFP become the same measure. We acknowledge, of course, that there are analogous measurement errors in capital input, which are likely correlated with errors in measured labor input and augment the impact. The main objective is to show that all the results about the change in TFP when only input measurement errors are considered remain qualitatively the same.

Denote a firm's true output, V^* (for value added), which includes observed output for current sale in the marketplace (denoted V) and unobserved output generated by productive activities intended to boost the firm's potential future revenue (denoted U). U can be regarded as unmeasured investment produced inhouse. We assume that U can be expressed as a weakly increasing function of V: $U = \Xi(V, \varepsilon)$, with $\partial\Xi/\partial V \geq 0$, and ε summarizes all the factors that influence U but are uncorrelated with V. This is a reasonable assumption to the extent that firms optimize their overall investment so that observed and unobserved investment move in the same direction. In the data, observed investment comoves positively with output.[44] Then, to a first-order approximation, the relationship in growth rates between V and U can be expressed as:

$$\mathrm{d}u = \xi \mathrm{d}v + \mathrm{d}\varepsilon \tag{28}$$

(as usual, log differences represent growth rates), where $\xi = (\partial\Xi/\partial V)(V/\Xi)$ is the elasticity of unobserved output with respect to observed output, while $\mathrm{d}\varepsilon$ summarizes all the movements in $\mathrm{d}u$ that are uncorrelated with $\mathrm{d}v$, which can include classical measurement errors. We further assume that $\mathrm{d}\varepsilon$ is also uncorrelated with any inputs.

Allowing the two types of output to differ, we can regard the growth of total output as a Divisia index of observed and unobserved output.[45] Then, we have the following expression for the growth rate of observed output $\mathrm{d}v$:

[44] The fact that firms generally do not take advantage of the theoretically lower opportunity cost of factor inputs to carry out more investment in downturns is consistent with the accumulated evidence of countercyclical financial frictions and the likely binding downward rigidity in wages in downturns. We elaborate further on this assumption in the next section.

[45] Their respective production functions may differ only in the growth rate of the Hicks-neutral technology term, or also in terms of factor shares, for example, U may require a higher share of skilled labor, such as shown in Wolff 2002.

$$\mathrm{d}v = \frac{1}{s_Y + (1-s_Y)\xi}\left[\mathrm{d}v^* - (1-s_Y)\mathrm{d}\varepsilon\right], \tag{29}$$

where s_Y is the nominal share of observed output in total output.

We assume that the true labor input (L^*) is a product of observed hours (L), which can be further decomposed into the number of workers (N), hours per worker (H), and unobserved effort (E): $L^* = (HN)E \equiv LE$ [46] This implies that the growth of observed labor input can be written as: $\mathrm{d}l = \mathrm{d}l^* - \mathrm{d}e$. As Basu and Kimball (1997) have shown, under fairly general conditions the unobserved effort is a monotonically increasing function of the observed number of hours per worker. A first-order approximation in growth rate yields: $\mathrm{d}e = \zeta \mathrm{d}h + \mathrm{d}\omega$, where ζ is the elasticity of effort with respect to hours per worker, while $\mathrm{d}\omega$ denotes any movements in $\mathrm{d}e$ uncorrelated with observed hours. We assume that $\mathrm{d}\omega$ is also uncorrelated with either $\mathrm{d}v$ or $\mathrm{d}\varepsilon$. Thus, any correlation between $\mathrm{d}u$ and $\mathrm{d}e$ is fully captured through their comovement with observed output ($\mathrm{d}v$) and labor input ($\mathrm{d}l$), respectively. Combining all the terms, we have the following relationship regarding labor input:

$$\mathrm{d}l = \mathrm{d}l^* - \zeta \mathrm{d}h - \mathrm{d}\omega. \tag{30}$$

Accordingly, we can derive the covariance between observed output and labor input in relation to the covariance between their unobserved counterparts as follows:

$$\mathrm{cov}(\mathrm{d}v, \mathrm{d}l) = \frac{1}{\left[s_Y + (1-s_Y)\xi\right]}\left[\mathrm{cov}(\mathrm{d}v^*, \mathrm{d}l^*) - \zeta\,\mathrm{cov}(\mathrm{d}v^*, \mathrm{d}h)\right]. \tag{31}$$

This in turn implies that the covariance between measured output and labor productivity growth ($\mathrm{d}a$) is as follows:[47]

$$\mathrm{cov}(\mathrm{d}v, \mathrm{d}a) = \mathrm{var}(\mathrm{d}v) - \mathrm{cov}(\mathrm{d}v, \mathrm{d}l) = \frac{\mathrm{var}(\mathrm{d}v^*) + (1-s_Y)^2\,\mathrm{var}(\mathrm{d}\varepsilon)}{\left[s_Y + (1-s_Y)\xi\right]^2} - \frac{\mathrm{cov}(\mathrm{d}v^*, \mathrm{d}l^*) - \zeta\,\mathrm{cov}(\mathrm{d}v^*, \mathrm{d}h)}{\left[s_Y + (1-s_Y)\xi\right]}. \tag{32}$$

If we measure the cyclicality of LP by its linear regression coefficient on VA growth, which equals the percentage change in LP accompanying a 1-percent change in VA, then the coefficient estimate $\hat{\beta}$ is as follows:

$$\hat{\beta} = 1 - \frac{\mathrm{cov}(\mathrm{d}v, \mathrm{d}l)}{\mathrm{var}(\mathrm{d}v)} = 1 - \frac{\left(1-\hat{\beta}^*\right)\mathrm{var}(\mathrm{d}v^*) - \zeta\,\mathrm{cov}(\mathrm{d}v^*, \mathrm{d}h)}{\left[\mathrm{var}(\mathrm{d}v^*) + (1-s_Y)^2\,\mathrm{var}(\mathrm{d}\varepsilon)\right] \Big/ \left[s_Y + (1-s_Y)\xi\right]}. \tag{33}$$

---

[46] We again ignore labor quality in these derivations because of its small overall contribution to labor input growth. What matters here is the correlation between changes in measurement errors of labor quality, if any, and output or other components of labor input. This correlation is likely to be minor.

[47] We ignore labor quality ($\mathrm{d}lq$) adjustment. Otherwise, the covariance between output and labor productivity should include an additional term: cov($\mathrm{d}v$, $\mathrm{d}lq$).

Here, we substitute out $\operatorname{cov}\left(\mathrm{d}v^*, \mathrm{d}l^*\right)$ using the true cyclicality of LP, $\hat{\beta}^*$:

$$\hat{\beta}^* = 1 - \operatorname{cov}\left(\mathrm{d}v^*, \mathrm{d}l^*\right) \Big/ \operatorname{var}\left(\mathrm{d}v^*\right).$$

Clearly, $\hat{\beta}$ is positively related to its accurately measured counterpart, $\hat{\beta}^*$, all else being equal. As discussed above, $\hat{\beta}^*$ may have declined since the mid-1980s for a number of reasons: for example, the variance of shocks may have fallen or the mix of (productivity versus demand) shocks may have changed. Even without a decline in $\hat{\beta}^*$, however, $\hat{\beta}$ can still fall because of the combined effect of the other arguments in (33). So a decline in $\hat{\beta}$, that is, less procyclical LP according to our definition above, can be the result of a higher covariance between true output and input, or a lower variance of the true output, or true noise. If we instead assume that all dynamics of the correctly measured variables have remained unchanged, then we can derive the following relationship between $\hat{\beta}$ and parameters s_Y, ξ, and ζ:

$$\partial\hat{\beta} \big/ \partial s_Y > 0 \text{ if } \xi > -\frac{\left[\left(1 - s_Y{}^2\right)\operatorname{var}\left(\mathrm{d}\varepsilon\right) + \operatorname{var}\left(\mathrm{d}y^*\right)\right]}{\left[\left(1 - s_Y\right)^2 \operatorname{var}\left(\mathrm{d}\varepsilon\right) - \operatorname{var}\left(\mathrm{d}y^*\right)\right]}, \text{ where } \operatorname{var}\left(\mathrm{d}\varepsilon\right) < \operatorname{var}\left(\mathrm{d}y^*\right) \Big/ \left(1 - s_Y\right)^2,$$

$$\partial\hat{\beta} \big/ \partial \xi < 0, \qquad \text{and } \partial\hat{\beta} \big/ \partial \zeta > 0. \tag{34}$$

For any given s_Y, (34) states that $\hat{\beta}$ would fall with ζ, meaning unobserved labor effort becomes less volatile relative to observed total hours. This condition, however, is not necessary if cyclicality is measured using the correlation of dv with da, as shown above, when the variance of da falls sufficiently. In contrast, $\hat{\beta}$ would fall as ξ rises, meaning unmeasured output becomes more volatile relative to measured output. The sign of $\partial\hat{\beta} \big/ \partial s_Y$ warrants special attention.[48] It is positive if ξ exceeds 1 by a sufficient margin, as spelled out in (34), where var(dε) is required to not exceed the variance of observed dy. In words, when the elasticity of unmeasured output with respect to measured output (ξ) is high, the estimated cyclicality of LP using observed output and input data will fall if the share of business activities devoted to producing market output falls. This is a plausible case when unmeasured output is small relative to measured output, so as the share of the former rises, observed cyclicality of LP falls. Otherwise, $\hat{\beta}$ would, in fact, rise as the share of unmeasured output rose.

[48] $$\frac{\partial\hat{\beta}}{\partial s_Y} = -\left[\frac{\operatorname{cov}\left(\mathrm{d}y^*, \mathrm{d}l^*\right)}{1+\zeta}\right] \frac{\left(1-\xi\right)\left[\operatorname{var}\left(\mathrm{d}y^*\right) + \left(1-s_Y\right)^2 \operatorname{var}\left(\mathrm{d}\varepsilon\right)\right] + 2\operatorname{var}\left(\mathrm{d}\varepsilon\right)\left(1-s_Y\right)\left[s_Y + \left(1-s_Y\right)\xi\right]}{\left[\operatorname{var}\left(\mathrm{d}y^*\right) + \left(1-s_Y\right)^2 \operatorname{var}\left(\mathrm{d}\varepsilon\right)\right]^2}.$$

In short, the derivations in this appendix aim to make it clear that, to the extent there exists non-negligible mismeasurement in either inputs or output, estimates of the cyclicality of labor productivity based on observed data can change when the relative importance or the relative volatility of either category of mismeasurement changes. This can occur even without any change in the intrinsic dynamics of the true inputs and output, which are unobserved or unobservable.

Appendix III. Estimation of the Utilization-Adjusted TFP

This appendix details the estimations used to derive utilization-adjusted TFP and discusses the parameter estimates. First, following BFK (2006), the input shares used to compute dx_{it} in equation (10) are time-series averages over the sample years for each industry; these input shares are viewed as a proxy for steady-state values.[49] The average hours per worker variable for each industry is detrended using the Christiano and Fitzgerald (2003) filter with the standard cycle frequency of two to eight years to remove a clear trend in the time-series of average hours per worker for most industries.[50] Detrending is necessary because dh is meant to serve as a proxy for cyclical variations in resource utilization.[51, 52] A dummy variable that equals 0 before 1973 and 1 afterward is included to account for the productivity slowdown, although it does not seem to be significant for most industry groups.

For precision, we estimate (10) using panels of industry groups; that is, restricting the slope parameters to be the same across industries within each group but allowing the intercept to differ using industry fixed effects.[53] We divide the industries into the following four groups (or sectors): i) nondurable

[49] Accounting for the downward trend of the labor share since the mid-1980s makes little difference for the estimates of dz_{it}, since using time-varying shares alters dx_{it} only slightly, consistent with the finding of Elsby, Hobijn, and Sahin (2013).

[50] In particular, it exhibits a downward trend for most service industries, largely because of the entry of women into the labor force, more of whom are part-time employees. For total manufacturing, average hours per worker first declined through the early 1980s and have since recovered partially, except for the two large dips during the 1991 and 2001 recessions.

[51] Fernald (2007) shows that it is important to take account of the low-frequency trend in the average hours series in estimating the impact of technology shocks when they are identified using long-run restrictions in VARs. Not accounting for the trend can change the sign of the estimate from negative to positive.

[52] Basu and Kimball (1997) show that hours per worker is a proxy for both labor effort and capital utilization if the cost of using capital more intensively includes a shift premium paid to workers. Data are hardly ever available to parse out how much of the contribution should be attributed to labor effort and how much to capital intensity. If, however, the cost of more intensive use of capital merely comprises faster appreciation, then capital utilization can be approximated using the rate of investment and the cost share of materials versus capital. In that case, hours per worker solely approximate the degree of labor effort.

[53] Industry-specific estimates are available upon request. The markup estimates are clustered between 0.5 and 1.3, with a few relatively extreme values on the low end. Industries with serious point estimates of decreasing returns to

manufacturing (seven industries, codes 15t16 to 25 in Table A.1), ii) durable manufacturing (six industries, codes 26 to 36t37), iii) construction (industry code F), and iv) the other 12 private industries (referred to as nonmanufacturing or services, although including utilities, corresponding to industry codes E to O, excluding L). Tests cannot reject the null hypothesis that the slope coefficients are equal across industries within each group.

Equation (10) is estimated using the limited information maximum likelihood method with demand-side instrumental variables for the two input terms on the right-hand side, because input use is most likely correlated with technology shocks. We use an updated version of the following three demand-side instrumental variables as in BFK (2006): real oil price shocks, real defense spending, and monetary policy shocks. The oil shock is specified as in Hamilton (1996): the maximum positive shock to the real price of oil (normalized by the GDP deflator) over the past four quarters. The series of monetary policy shocks is identified according to the structural VAR in Christiano, Eichenbaum, and Evans (2005).[54] The fiscal policy shocks are measured using the growth rate of real government defense spending, as proposed in Hall (1988) and Ramey (1989).[55] Each of these instrumental variables is an annual measure equal to the four-quarter average lagged by two quarters.

For the conservative baseline estimate of the utilization coefficient β_i when μ_i is restricted to 1, reported in Table 1, the sample period is 1950 to 2007 to match the sample used for most of the pre- versus post-1984 comparison analyses. β_i is estimated most precisely for durable manufacturing and less so for the other two industry groups. It is rather imprecisely estimated for the construction industry by itself, which is typical of the (unreported) industry-specific estimates of this parameter.

Table 2 reports the alternative parameter estimates without the CRS constraint. We remark on two features of the estimates: 1) the markup (or returns to scale) estimate is not significantly different from one for any industry group, although it is more distinctly greater than one for durable

---

scale are mining and quarrying (C), utilities (E), and financial intermediation. These industries seem to be special in some way to render their markup estimates problematic: the output of mining and quarrying is largely commodities, utilities are heavily regulated, and the output of financial intermediation is poorly measured. The utilization coefficient β_i is estimated rather imprecisely for many industries, especially chemicals, rubber, and plastic, all of which feature continuous-process production.

[54] We also experimented with two other measures of monetary policy shocks: one is constructed by Romer and Romer (2004) as deviations from the Federal Reserve's intended changes in the fed funds rate around FOMC meetings, while controlling for the forward-looking behavior using the Fed's own Greenbook forecast; this measure was later updated by Coibon for 1997 to 2003; the other is shocks to the fed funds futures rate from FOMC policy announcements as proposed by Kuttner (2001). They make no qualitative difference to our results.

[55] Changes in real government defense spending are not necessarily all unforeseen shocks, as demonstrated by Ramey (2011). Being anticipated does not render them invalid as demand IVs, however, as long as they are uncorrelated with technology shocks, which affect changes in output without any change in input.

manufacturing and less than one for nondurable manufacturing and services; 2) the utilization coefficient β_i differs from its counterpart reported in Table 1 in intuitive ways: when the markup estimate exceeds one, the β_i estimate falls, and vice versa. It is not surprising that measured and unmeasured inputs are substitutable in producing output. This helps to explain why the technology shock series derived using either set of coefficient estimates behave similarly in the decompositions and regressions analyzed next.

Given the observation that cyclical dynamics for multiple variables appear to have changed around the mid-1980s, we also experimented with an alternative set of estimates where the slope coefficients are allowed to change after 1984. These coefficients are all rather imprecisely estimated, especially for nondurable manufacturing, and thus insignificant. We therefore proceed with the assumption that the production function relationship has not changed significantly since the mid-1980s.

With the parameters estimated, $\mathrm{d}z_{it} = \mathrm{d}y_{it} - \left(\mu_i \mathrm{d}x_{it} + \beta_i \mathrm{d}h_{it}\right)$ yields the true technology term for each industry, which equals the residual from (10) plus the industry-specific intercept and the post-1973 term. As explained above, our baseline case sets $\mu = 1$ for all industries. To be conservative, we set β to zero for the financial intermediation (FI) industry (code J) so that it does not contribute to the decomposition, since its output is rather poorly measured. We note, however, that this extra caution does not alter any results below qualitatively: similar results are obtained in robustness checks where we use the service industries' β for the FI industry or exclude the FI industry from the aggregate. Growth rates of TFP, technology, and utilization for all nonfarm business industries, along with the selected industries and industry groups, are plotted in Figure 1, along with the growth of VA, primary input, and employment.

Table A.1 Industry composition of Jorgenson KLEMS dataset

Industry Name	Code
TOTAL INDUSTRIES	*TOT*
AGRICULTURE, HUNTING, FORESTRY AND FISHING	AtB
MINING AND QUARRYING	C
TOTAL MANUFACTURING	*D*
FOOD , BEVERAGES AND TOBACCO	15t16
TEXTILES, TEXTILE , LEATHER AND FOOTWEAR	17t19
WOOD AND OF WOOD AND CORK	20
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	21t22
CHEMICAL, RUBBER, PLASTICS AND FUEL	*23t25*
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical products	24
Rubber and plastics	25
OTHER NON-METALLIC MINERAL	26
BASIC METALS AND FABRICATED METAL	27t28
MACHINERY, NEC	29
ELECTRICAL AND OPTICAL EQUIPMENT	30t33
TRANSPORT EQUIPMENT	34t35
MANUFACTURING NEC; RECYCLING	36t37
ELECTRICITY, GAS AND WATER SUPPLY	E
CONSTRUCTION	F
WHOLESALE AND RETAIL TRADE	*G*
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52
HOTELS AND RESTAURANTS	H
TRANSPORT AND STORAGE AND COMMUNICATION	*I*
TRANSPORT AND STORAGE	60t63
POST AND TELECOMMUNICATIONS	64
FINANCE, INSURANCE, REAL ESTATE AND BUSINESS SERVICES	*JtK*
FINANCIAL INTERMEDIATION	J
REAL ESTATE, RENTING AND BUSINESS ACTIVITIES	*K*
Real estate activities	70
Renting of m&eq and other business activities	71t74
COMMUNITY SOCIAL AND PERSONAL SERVICES	*LtQ*
PUBLIC ADMIN AND DEFENCE; COMPULSORY SOCIAL SECURITY	L
EDUCATION	M
HEALTH AND SOCIAL WORK	N
OTHER COMMUNITY, SOCIAL AND PERSONAL SERVICES	O
PRIVATE HOUSEHOLDS WITH EMPLOYED PERSONS	P

Table A.2 Summary Statistics of Industry Input and Output Growth rates and Factor Shares

Panel A. 27 Nonfarm business Industries, 1950–2007

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**N**	**Mean**	**S.D.**	**Min**	**Max**
Gross output	1,566	3.320	5.518	-24.56	40.15
Value added	1,566	3.397	10.12	-124.0	128.0
Capital	1,566	4.336	3.706	-17.77	22.18
Labor	1,566	1.367	4.061	-16.61	20.82
Total hours	1,566	0.981	4.128	-17.09	20.24
Employment	1,566	1.188	3.833	-16.55	19.43
Average hours	1,566	-0.208	1.417	-6.306	8.551
Detrended average hours	1,566	0.0184	1.131	-5.400	7.310
Intermediate input	1,566	3.482	8.837	-56.61	115.1
Composite input (time-varying weights)	1,566	2.845	5.141	-28.75	42.91
Composite input (time average weight)	1,566	2.885	5.333	-23.02	61.68
Primary input	1,566	2.267	3.338	-12.35	17.23
Labor productivity	1,566	2.417	9.737	-118.9	132.4
TFP (time-varying weights)	1,566	0.475	3.065	-16.95	18.87
TFP (time-average weight)	1,566	0.435	3.222	-21.54	22.26
TFP (time-varying weights), VA-basis	1,566	1.130	9.657	-124.6	129.9
Wage rate	1,566	2.155	6.088	-48.18	39.19
Labor share (% of revenue)	1,566	31.79	12.67	2.399	63.59
Capital share	1,566	17.41	14.21	2.040	83.46
Intermediate input share	1,566	50.80	15.62	14.07	92.27

Notes: This table reports the summary statistics of input and output growth rates in 1950–2007, all in percentage terms, for the 27 nonfarm business industries used in the industry-level analysis. The factor shares are all as a percentage of revenue.

Panel B. All industries, 1950–2007

VARIABLES	(1) N	(2) Mean	(3) S.D.	(4) Min	(5) Max
Gross output	1,740	3.138	5.438	-24.56	40.15
Value added	1,740	3.129	9.903	-124.0	128.0
Capital	1,740	4.078	3.795	-17.77	22.18
Labor	1,740	1.192	4.358	-22.29	49.82
Total hours	1,740	0.793	4.422	-20.69	49.66
Employment	1,740	0.983	4.012	-18.19	34.33
Average hours	1,740	-0.190	1.538	-6.306	15.33
Detrended average hours	1,740	0.0211	1.242	-5.541	12.11
Intermediate input	1,740	3.408	8.956	-56.61	115.1
Composite input (time-varying weights)	1,740	2.707	5.192	-28.75	42.91
Composite input (time average weight)	1,740	2.756	5.428	-23.02	61.68
Primary input	1,740	2.093	3.395	-12.35	20.29
Labor productivity	1,740	2.336	9.722	-118.9	132.4
TFP (time-varying weights)	1,740	0.431	3.170	-16.95	18.87
TFP (time-average weight)	1,740	0.382	3.348	-23.40	22.26
TFP (time-varying weights), VA-basis	1,740	1.036	9.506	-124.6	129.9
Wage rate	1,740	2.139	6.587	-48.18	39.19
Labor share (% of revenue)	1,740	31.50	12.35	2.399	63.59
Capital share	1,740	18.09	13.82	2.040	83.46
Intermediate input share	1,740	50.42	15.00	14.07	92.27

Notes: This table reports the same set of statistics as in Panel A for all of the 30 industries (excluding private households with employed persons) in the dataset compiled by Jorgenson et al.

Figure A.1 Share of nonfarm business industries in total VA of all industries

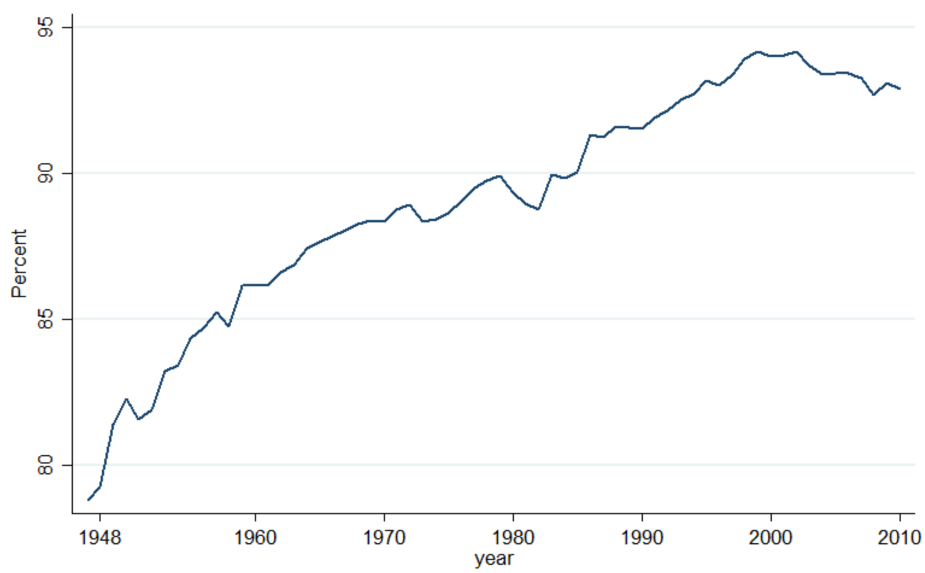


Table B.1a Cyclical correlation between labor productivity and output (VA): 1950–2010

Filter	1950 - 2010	1950 - 1983	1984 - 2010	Subperiod Diff.
Bandpass	0.350	0.428	0.042	-0.386
CF	0.367	0.430	0.197	-0.233
HP	0.303	0.420	-0.008	-0.428
First Difference	0.531	0.64	0.173	-0.467

Table B.1b Cyclical correlation between labor productivity and primary inputs: 1950–2010

Filter	1950 - 2010	1950 - 1983	1984 - 2010	Subperiod Diff.
Bandpass	-0.185	-0.089	-0.475	-0.386
CF	-0.19	-0.125	-0.331	-0.206
HP	-0.262	-0.101	-0.575	-0.474
First Difference	0.058	0.206	-0.271	-0.477

Note: Bandpass filter with frequency band 2–8 years. HP: Hodrick-Prescott filter with $\lambda = 6.25$.
CF: Christiano-Fitzgerald (2003) filter, with frequency band 2–8 years.

Table B.2a Cyclical correlation between TFP and output (VA): 1950–2010

Filter	1950 - 2010	1950 - 1983	1984 - 2010	Subperiod Diff.
Bandpass	0.763	0.810	0.488	-0.322
CF	0.769	0.818	0.613	-0.205
HP	0.729	0.805	0.445	-0.360
First Difference	0.804	0.874	0.539	-0.335

Table B.2b Cyclical correlation between TFP and primary inputs: 1950–2010

Filter	1950 - 2010	1950 - 1983	1984 - 2010	Subperiod Diff.
Bandpass	0.276	0.363	-0.087	-0.450
CF	0.277	0.353	0.101	-0.252
HP	0.205	0.356	-0.184	-0.540
First Difference	0.372	0.497	0.076	-0.421

Note: Bandpass filter with frequency band 2–8 years. HP: Hodrick-Prescott filter with $\lambda = 6.25$.
CF: Christiano-Fitzgerald (2003) filter, with frequency band 2–8 years.

Table B.3a Cyclical correlation between utilization-adjusted TFP and output: 1950–2010

Filter	1950 - 2010	1950 - 1983	1984 - 2010	Subperiod Diff.
Bandpass	-0.402	-0.470	-0.302	0.168
CF	-0.515	-0.578	-0.429	0.149
HP	-0.425	-0.476	-0.373	0.103
First Difference	-0.236	-0.331	-0.114	0.217

Table B.3b Cyclical correlation between utilization-adjusted TFP and primary inputs: 1950–2010

Filter	1950 - 2010	1950 - 1983	1984 - 2010	Subperiod Diff.
Bandpass	-0.322	-0.236	-0.512	-0.276
CF	-0.439	-0.307	-0.632	-0.325
HP	-0.373	-0.249	-0.568	-0.319
First Difference	-0.218	-0.182	-0.291	-0.109

Note: Bandpass filter with frequency band 2–8 years. HP: Hodrick-Prescott filter with $\lambda = 6.25$.
CF: Christiano-Fitzgerald (2003) filter, with frequency band 2–8 years.

Table B.4 Responses of output and inputs to technology shocks: before 1984 and the change afterward (based on unconstrained production function coefficients reported in Table 2)

RHS	(1) VA	(2) Inputs	(3) Total hours	(4) Employment	(5) Detrended hours	(6) Utilization	(7) TFP (VA-basis)	(8) LP	(9) Implicit VA deflator
dz	-0.361	-0.0913	-0.236	-0.0405	**-0.197*** **	**-1.333*** **	**-0.269***	-0.125	-0.109
	[0.241]	[0.146]	[0.196]	[0.175]	**[0.0348]**	**[0.150]**	**[0.139]**	[0.125]	[0.223]
$dz*D_{post84}$	0.546*	0.0855	0.127	0.113	**0.0291**	**0.580*** **	**0.461*** **	0.418***	-0.0336
	[0.288]	[0.204]	[0.268]	[0.232]	**[0.0432]**	**[0.174]**	**[0.161]**	[0.160]	[0.243]
dz(-1)	-0.106	-0.243	-0.518**	-0.472**	**-0.0403**	**0.112**	**0.138**	0.411***	-0.523**
	[0.273]	[0.166]	[0.223]	[0.199]	**[0.0395]**	**[0.170]**	**[0.158]**	[0.142]	[0.253]
$dz(-1)*D_{post84}$	0.113	0.181	0.348	0.339	**0.0297**	**0.0180**	**-0.0699**	-0.235	0.345
	[0.313]	[0.215]	[0.284]	[0.247]	**[0.0466]**	**[0.190]**	**[0.176]**	[0.171]	[0.270]
dz(-2)	0.997***	0.390**	0.524**	0.409**	**0.128*** **	**0.707*** **	**0.609*** **	0.474***	-0.663***
	[0.268]	[0.163]	[0.219]	[0.196]	**[0.0388]**	**[0.167]**	**[0.155]**	[0.139]	[0.249]
$dz(-2)*D_{post84}$	-0.808***	-0.275	-0.461	-0.381	**-0.0632**	**-0.473*** *	**-0.534*** **	-0.348**	0.446*
	[0.313]	[0.218]	[0.287]	[0.250]	**[0.0468]**	**[0.190]**	**[0.175]**	[0.172]	[0.268]
dz(-3)	0.402	0.324**	0.313	0.312*	**0.0300**	**0.185**	**0.0790**	0.0894	-0.725***
	[0.256]	[0.156]	[0.209]	[0.187]	**[0.0370]**	**[0.159]**	**[0.148]**	[0.133]	[0.237]
$dz(-3)*D_{post84}$	-0.376	-0.258	-0.324	-0.286	**-0.0124**	**-0.212**	**-0.118**	-0.0518	0.644**
	[0.310]	[0.221]	[0.290]	[0.251]	**[0.0466]**	**[0.187]**	**[0.172]**	[0.172]	[0.261]
dz(-4)	0.265	0.158	0.102	0.138	**0.00124**	**0.241**	**0.108**	0.163	-0.350
	[0.248]	[0.151]	[0.202]	[0.181]	**[0.0359]**	**[0.154]**	**[0.143]**	[0.129]	[0.230]
$dz(-4)*D_{post84}$	-0.285	-0.264	-0.263	-0.258	**0.0126**	**-0.176**	**-0.0221**	-0.0218	0.291
	[0.297]	[0.210]	[0.277]	[0.240]	**[0.0446]**	**[0.179]**	**[0.166]**	[0.165]	[0.251]
D_{post84}	1.585	1.114	1.075	0.591	**0.00492**	**0.700**	**0.480**	0.509	-5.425***
	[1.784]	[1.252]	[1.650]	[1.433]	**[0.267]**	**[1.080]**	**[0.998]**	[0.986]	[1.519]
Constant	0.908	1.594*	1.145	1.320	**0.141**	**-0.0807**	**-0.695**	-0.238	9.309***
	[1.513]	[0.919]	[1.234]	[1.103]	**[0.219]**	**[0.940]**	**[0.873]**	[0.784]	[1.402]
$\sigma*D_{post84}$	-1.041***	-0.260	-0.413	-0.456*	**-0.127*** *	**-0.722*** **	**-0.686*** **	-0.394**	-1.352***
	[0.338]	[0.239]	[0.315]	[0.273]	**[0.0508]**	**[0.205]**	**[0.189]**	[0.187]	[0.287]
σ(resid.)	2.312***	1.403***	1.884***	1.684***	**0.334*** **	**1.436*** **	**1.334*** **	1.197***	2.141***
	[0.285]	[0.173]	[0.232]	[0.207]	**[0.0411]**	**[0.177]**	**[0.164]**	[0.147]	[0.263]
Observations	57	57	57	57	**57**	**57**	**57**	57	57
chi2	20.79	14.43	17.87	17.37	**116.0**	**208.6**	**32.03**	33.18	37.06

Notes: Heteroscedasticity robust standard errors in brackets. The notation for coefficient significance: *** p<0.01, ** p<0.05, * p<0.1.