Vanishing Procyclicality of Productivity? Industry Evidence

J. Christina Wang

Abstract:

Labor productivity (LP) in the U.S. has gone from being procyclical to acyclical over the past 20 years. 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 time period. This paper then uses industry-level data to explore the reason for the change in the cyclicality of productivity, and assess the plausibility of models that have been offered to explain the change. It further decomposes TFP into technical change and utilization. It finds that the main reason for the decline in the productivity-input correlation is an increase in the importance of technology shocks as a contributor to measured changes in productivity, combined with the short-run negative correlation between technology improvement and input use. The facts are consistent with the hypothesis that both internal and external labor markets have become more flexible, reducing the cost to firms of adjusting employment and also of varying the utilization of existing labor and capital.

Keywords: Productivity, Technology, Business cycle, Persistence, 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. Additional thanks to John Fernald for making his quarterly TFP and utilization-adjusted TFP data available online. 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 Chris Kask of the Bureau of Labor Statistics for his most generous assistance with the BLS manufacturing data.

This version: July 10, 2014

I. Introduction

During the recent deep recession, U.S. labor productivity took a sharp but brief dive for three quarters surrounding the height of the financial crisis in 2008:Q4. It then recovered to a brisk pace of over three percent per annum on average over the first six quarters of the recovery, although it has since slowed to a tepid rate of below one percent. 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 brought about renewed interest in understanding the changing cyclicality of productivity.

A number of papers have investigated the aggregate facts, and proposed mechanisms that may explain the observed changes. However, these papers have examined only aggregate time-series data. And they rely entirely on dynamic stochastic general equilibrium models for identification—different structural models of the economy implies different relationship among economic variables in terms of volatility and comovement. This study thus proposes to utilize the cross-industry dimension as an alternative and complementary method of identifying the mechanisms that have led to the diminished procyclicality of labor productivity. Industries differ in their technology, labor market institutions, sensitivity to monetary policy, and time series of technology and demand shocks, as well as how these attributes change over time. These differences imply that each proposed mechanism should have differing degrees of relevance across industries. Hence, cross-industry differences in the change of the cyclical property of productivity can shed more light on which proposed mechanisms are responsible for the change and their relative importance. It should of course be noted that an industry-level analysis may not offer additional identification if the structural change being investigated occurs uniformly across industries.

Moreover, disaggregated data are better suited to account for the contribution of unmeasured input utilization to productivity growth and uncover the true technology term. We will then be able to evaluate to what extent changes in the cyclical property of technology shocks versus utilization have contributed to the change in productivity's cyclicality. With industry data, we will also be able to decompose changes in the cyclicality of aggregate productivity into a weighted average of within-industry changes versus changes in correlations across industries. This may offer further clues as to the forces behind the aggregate change. For example, if the diminished procyclicality of labor productivity is more due to cross-industry correlations, then it seems less likely that greater labor market flexibility, for

example, is the dominating force behind the aggregate change.

Applying a method developed in previous studies, we correct total factor productivity (TFP) for unmeasured input utilization to evaluate relative contribution of technology and utilization to the change in productivity's cyclical dynamics. We then discover that the cyclicality of technology has changed little. The main reason for TFP's lower correlations with output and inputs is that the technology term, which has remained countercyclical throughout the sample period, accounts for a larger share of TFP's correlation with inputs after the mid-1980s.

In fact, we find evidence both in the aggregate and at the industry level that inputs, especially average hours per worker, which under plausible conditions is a proxy for utilization, *contract* more in response to a positive technology shock in the period since the mid-1980s even though the shocks are no less persistent. This finding warrants more analysis since it is potentially inconsistent with the notion that monetary policy has improved in its accommodation of technology shocks. Utilization's effect, however, is more than offset by the greater contribution from the technology term so that overall TFP responds more positively, and thus becomes less correlated with inputs and output over this period.

This paper is, of course, not the first to investigate the changing behavior of labor productivity. Gali and van Rens (2010) explore the declining correlation between aggregate output and labor productivity, and propose an explanation based on the hypothesis that firms can now change employment at lower cost.[1] This change in labor market dynamics matters for the *measured* cyclicality of productivity because unobserved labor and capital input make labor productivity and TFP more procyclical, since we cannot accurately measure variations in factor inputs over time. This "contamination" from unmeasured inputs was noted by Solow (1964) long ago. In the story of Gali and van Rens, labor market institutions have become more flexible, and so more of the adjustment to a shock is accomplished through employment instead of effort. In other words, there is less labor hoarding now than there was before. The reduction in utilization reduces the positive correlation between measured productivity and employment. McGratten and Prescott (2007, 2012) also notice the disappearing positive correlation between output and labor productivity, but they propose a different explanation. Their mechanism is based on the changing degree of measurement error in the observed output.

[1] In addition, Gordon (2010), Barnichon (2008), Galí and Gambetti (2009), and Nucci and Riggi (2009), using different approaches, have all independently investigated the potential sources of the decline in the correlation between labor productivity and hours.

We find that employment has not become more responsive than average hours per worker to technology shocks since the mid-1980s. This fact is inconsistent with an explanation purely based on lower hiring and firing costs, as in Gali and van Rens (2010). On the other hand, there is a robust relationship across industries between the decline in TFP's correlation with inputs and output and the relative increase in the volatility of employment and total hours vis-à-vis value added. These findings together suggest that both external and internal labor markets may have undergone reforms that enhance flexibility, thus enabling firms to reduce the cost of adjusting both extensive and intensive margins of labor. At the same time, the more flexible labor market seems to have mostly led to more efficient input adjustments *within* individual industries. When we decompose aggregate TFP into technology, utilization and resource-allocation terms, we find that the latter two combined can account for only about a quarter of the reduction in the procyclicality of TFP.

Apart from explanations that are predicated on measurement errors, other structural changes to the economy can also bring about a change in the response of inputs to productivity shocks and in turn the correlation between output and labor productivity. In particular, how monetary policy reacts to shocks in the economy affects the response of economic variables, both nominal and real, to those shocks. For example, Gali (1999) and Basu, Fernald and Kimball (BFK, 2006) have presented evidence that technology improvements are contractionary in the short run, and interpret this finding as consistent with a business cycle model with nominal price rigidity. In a typical sticky-price model, however, technology improvements would cease to be contractionary if the monetary authority accommodated them fully. In fact, Gali, Lopez-Salido and Valles (2003) have shown that since the mid 1980s economic activity indeed exhibits less of a contraction following a positive technology shock, and they interpret this fact as evidence that the conduct of the U.S. monetary policy has improved over that period.

Absent measurement errors, the hypothesis of Gali et al (2003) actually implies that productivity would most likely comove *more* positively with output rather than less, since a higher correlation between inputs and productivity boosts the correlation between output and productivity, all else being equal. Gali and van Rens (2010) solve this problem by having a preference shock that leads to countercyclical productivity because of decreasing returns to scale to labor. Alternatively, this observation may indicate that since the mid-1980s the central bank has become more adept at accommodating the permanent component of technology shocks, which is the type identified in Gali et al. (2003), but not the more transitory components, which are included in the technology shocks identified

by the method used in this study. It is also possible that other changes, such as those related to input or output measurements discussed above, more than offset the effect due to better monetary policy.

The remainder of this paper is organized as follows. Section 2 presents briefly the evidence based on aggregate data for the diminishing procyclicality of labor productivity. Section 3 then discusses mechanics that can potentially lower the positive comovement between output and productivity, and presents some additional evidence in aggregate data that supports the hypothesis of less labor hoarding. Section 4 presents industry-level evidence for the role of reduced labor hoarding in the vanishing procyclical of labor productivity. Section 5 concludes.

II. Diminished Procyclicality of Productivity? Aggregate Evidence

We start with a summary of the evidence based on aggregate data for the change, if any, in the cyclical comovements between output and the various measures of productivity—labor productivity (LP), total factor productivity (TFP) and utilization-adjusted TFP.

2.1 Diminished Procyclical of Labor Productivity

We begin with the cyclicality of labor productivity, since this is the cyclical relationship that most previous studies have focused on. As Gali and van Rens (2010) show, the correlation between labor productivity and aggregate output at the business cycle frequency has declined since around the middle of 1980s. To extract the cyclical component of output and labor productivity, they apply a bandpass filter and the fourth-difference filter to (the logarithm of) quarterly data. The bandpass filter features the standard frequency bands—extracting fluctuations with frequencies between six and thirty-two quarters.[2] Figure 1 reproduces the time series of bandpass filtered quarterly output and labor productivity (both in logs) for the private business sector, along with the corresponding series of total factor productivity 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:Q1. This exact date is chosen mainly to

[2] The fourth-difference filter, which yields four-quarter growth rates, is by comparison somewhat arbitrary. Gali and van Rens (2010) justify its use by referring to Stock and Watson (2002), who in fact simply argue that the first-difference operator yields the highest frequency fluctuations, which are too high and not relevant for business cycle analysis. To the extent that seasonal movements are present at the quarterly frequency, then fourth-difference can also further reduce their influence.

be consistent with the choice in Gali and van Rens (2010). It coincides also with the timing that is commonly identified in the literature (see e.g. Stock and Watson, 2002) as the break dates when the volatility of aggregate real economic variables fell significantly. As we will see later, it is not too far from the break date identified by formal statistical tests.

Table 1 reports the correlation between aggregate output and labor productivity growth for all the sample periods still available after detrending (for instance, the bandpass filter removes 12 quarters at each end of the time series), which are 1950:Q1 to 2009:Q2 for quarterly data and 1950 to 2009 for annual data. It also computes the correlation for two subperiods 1960 to 1983 and 1984 to 2007, separately.[3] The total panel reports the correlation coefficients for quarterly data while the bottom panel reports for annual data, which are included mainly to serve as a benchmark for the analysis later using industry level data that are only available at annual frequency. The first row of each panel reports the correlation estimated using bandpass-filtered data, exactly comparable with the data used by Gali and van Rens (2010). We observe a substantial reduction in the correlation coefficient before and after 1984, from about 0.6 to essentially zero.

Table 1a reports the same statistics, but for a shorter time series, from 1960:Q1 to 2007:Q4, again to provide a benchmark for the analysis later using industry level data that are only available over 1960 to 2007. For labor productivity, the magnitude of the decline in correlation since the mid 1980s remains essentially the same for this shorter time period, and in fact slightly steeper for the quarterly data.

Going beyond the previous studies, here we conduct formal tests to investigate if there have been structural breaks in the relationship between detrended output and labor productivity. The key methodological advantage of these tests is that they explicitly take account of the uncertainty regarding the timing of a change or changes in the relationship across variables. Table 1 reports the test statistics of formal Bai-Perron (1998, 2003) structural break tests on the bandpass filtered quarterly output and labor productivity data.[4] We consider two cases: 1) only the slope coefficient of regressing bandpass-detrended LP on detrended output is allowed to change whereas the intercept is assumed to remain constant, versus

[3] This is sample period is chosen to coincide with the years during which the industry data set is available. Results based on the full time series of aggregate data – 1947 to 2012 – does not change qualitatively. Not including the financial crisis and the ensuing deep recession and slow recovery increases the difference between two subperiods.

[4] It is not strictly correct to test whether the relationship between two integrated series has changed by first filtering them separately and then testing for structural breaks between the two filtered series. Future versions will also examine the break test developed in Bai, Lumsdaine and Stock (1998) that is applicable to variables that may contain a stochastic trend, although no tests are yet available for multiple breaks in regressions involving integrated regressors, according to Perron's (2005) review of structural break tests.

2) both the intercept and the slope are allowed to change.[5] We conduct the test both for the period 1960:Q1 to 2007:Q4 and the full available sample period of 1950:Q1 - 2009:Q2 and results are qualitatively the same, so we only discuss test results pertaining to the full sample period.[6]

When only the slope coefficient is allowed to change, the double maximum test (for the null of no break against the alternative of an unknown number of breaks) statistic equals 4.42, while the critical value at the 10% level is 7.46. The supF test of one break, against the null of no break, identifies 1986:Q3 as the (insignificant) break date. However, when both the intercept and the slope are allowed to change, the test can reject the null of no break at the 1% level. The break date identified is similar, around the end of 1986.[7] The different test results depending whether the intercept is allowed to change may be relate to findings in previous studies (see for example Fernald 2007 and Perron and Wada 2009) that there has been at least one break in the trend growth rate of output around the mid 1970s. Overall, the Bai-Perron test seem to indicate some uncertainty regarding whether there has been a significant change in the relationship between LP and output once uncertainty regarding the timing of possible breaks is taken into consideration.

As a robustness check, we also conduct another trend break test developed by Elliot and Muller (2006). The advantage of this test is that it is asymptotically equivalent and efficient for a large class of persistent breaking processes so that in the limit there is no need to know the exact breaking process.[8] As reported in Table 2, the Elliot-Muller (2006) test applied to bandpass filtered quarterly series of output and labor productivity can reject, at the 10% level, the null hypothesis that there is no change in the coefficient of regressing the cyclical component of productivity on output at the 10% level for the sample of 1950:Q1 to 2009:Q2.[9] However, if we truncate the sample to end in 2007:Q3, leaving out the recent deep recession, the test can reject the null at basically the 10% level: -7.744 versus the 10% critical value of -7.14.

By comparison, if we simply regress the cyclical component of labor productivity on output and its interaction with a post-1984 dummy, and test if the coefficient on the interaction term is significantly

[5] The baseline Matlab programs for conducting the test were downloaded from Pierre Perron's website (http://people.bu.edu/perron/code.html) on September 4, 2012.
[6] The bandpass filter removes 12 quarters at each end of the time series.
[7] If the sample period is divided at the test identified "break date" of 1986:Q3, the change in correlation coefficient over the two subperiods is basically the same as reported in Table 1, which divides at 1984:Q1.
[8] Moreover, it is "valid for a wide range of data-generating processes and has good power and size properties even in heteroscedastic models," according to Christiano and Fitzgerald (2003).
[9] The test statistic is -6.272, while the 10% critical values is -7.14.

different from zero, which is equivalent to a Chow test, then we find that it is significantly negative (at the 5% level).[10] In fact it is sufficiently negative that the slope coefficient falls to zero for the post-1984 period, meaning that labor productivity no longer comoves with output since then. The reason that a Chow test indicates a significant decline in the coefficient whereas the formal structural break tests discussed above tend to be less clear-cut is that the former ignores the uncertainty regarding the break date or dates. For the same reason, this is also why the test of a change in the correlation coefficient, such as in Gali and van Rens (2010), turns up significant when the break date is predetermined. Not surprisingly, once that uncertainty is also taken into account, the significance of the change in the correlation falls substantially. In general, one should explicitly account for the uncertainty regarding the timing of any changes in the relationship investigated unless there is indisputable evidence that a specific event or set of events have resulted in a structural change.

In sum, there is reasonable evidence that the relationship between bandpass filtered output and labor productivity has changed around sometime in the mid 1980s. The break in cyclicality, however, is just about statistically discernible once we take explicit account of the uncertainty regarding the timing of such a break.

2.1.1 Robustness to Different Filters

The pattern reported above turns out to be fairly robust in that it remains qualitatively the same using data filtered with different methods. This is not guaranteed a priori, since Canova (1998) shows that several of the so-called business-cycle stylized facts are not robust to different detrending methods. In rows two and three of Table 1, we report that the change in correlation coefficients over the two subperiods divided at 1984:Q1 is similar when data are filtered using two other commonly applied filters: the Hodrick-Prescott (HP, 1980) filter and the Christiano-Fitzgerald (CF, 2003) filter, which is a different finite-sample approximation to the ideal bandpass filter.[11, 12] The similarity is greater when using the longer sample of 1950 to 2009 than using the sub-sample of 1960 to 2007, which is chosen to match the

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[10] The standard errors are computed using the Newey-West (1987) estimator to account for possible serial correlation and heteroscedasticity (since it has been shown that the real macroeconomic variables have become less volatile since the mid 1980s, at least until the recent deep recession).

[11] The version of the CF filter used here is the simplified approach "based on the generally false assumption that the data are generated by a random walk," which they found to be nearly optimal.

[12] Canova (1998) considers many other filters in addition to the HP and the bandpass-type filters, 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. This possibility will be explored further in future updates of this study.

analysis later using industry data. In particular, in the shorter sample, the CF-filtered annual data yield a noticeably smaller decline in the LP-VA correlation than data filtered with all the other methods, as will be confirmed by the industry data.

It is probably not surprising that these different filters produce similar declines in the cyclical correlation between aggregate LP and VA, since the bandpass filter and the HP filter, both assigned the parameter values standard in business cycle analysis, have similar gain functions when applied to difference-stationary time series.[13] The main difference is that the HP filter retains a little more of the high frequency and the extreme low frequency movements. This turns out to not make much difference, which may be surmised given the finding by Gali and van Rens (2010) that the decline in correlation is basically as evident in the fourth-differenced data, which retains more of the annual frequency fluctuations.

None of the filtering processes discussed above explicitly considers the possibility of a trend break in the time series. On the other hand, statistical tests have generally indicated that there was a break in the trend growth rate of labor productivity and output around 1973, and to a much lesser degree another break sometime between 1995 and 1997 (see e.g. Fernald 2007 and Perron and Wada 2009). As Perron and Wada (2009) show, when this trend break is ignored, the two detrending methods they consider — the Beveridge-Nelson versus the unobserved component model — yield significantly different trend-cycle decomposition. In contrast, once the possibility of trend break is taken into account, these two detrending models yield essentially the same results.

To allow for the possibility of trend breaks in the growth rates of either output or labor productivity, we adopt a method that is a simplified approximation to the detrending models used by Perron and Wada (2009). They show that the trend-cycle decomposition from the unobserved component model allowing for trend breaks can be well approximated by a HP filter with an extremely large value of λ equal to 800,000 for quarterly data. This produces trend growth rates that are far less variable compared to the standard choice of $\lambda = 1600$, and thus leaves more of the actual fluctuations in the cyclical component. As shown in Table 1, this filter turns out not to alter the qualitative conclusion that there has been a noticeable decline in the correlation between output and labor productivity around the mid 1980s.

The last filter we check is the simplest first-difference operator, which is equivalent to computing

[13] In the case of a linear filter such as the bandpass, the directly filtered labor productivity 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.

the quarter-over-quarter growth rate. This filter yields stationary series to the extent that the series have no more than one unit root, but it has the disadvantage of leaving out cycles of all but the highest frequency. In this case, it appears that the quarterly growth rates of output and labor productivity are just as correlated in recent years as they were in the 1960s and 1970s, as shown in Table 2. This suggests that at the very high quarterly frequency, whatever forces may have induced the change in the comovement between output and productivity is not operative. We will return to this point later when we discuss the plausible mechanisms for the change in the cyclical relationship.

2.2 Cyclicality of Total Factor Productivity

We next discuss the evidence for any change in the cyclical comovement between total factor productivity and aggregate output of private business sector at the quarterly frequency.[14] As we will see, its difference from the LP-output correlation lies in the covariance between capital deepening and output, as well as the relative change in the variance of LP versus TFP growth, which is ultimately to the relative change in variance between capital and labor growth. We apply the same set of methods for trend-cycle decomposition as used above for labor productivity. Table 3 reports the correlation coefficients for 1950 to 2009 and the two subperiods divided at 1984:Q1; the top panel uses quarterly data while the bottom panel uses annual data. Comparing Table 3 with Table 2 reveals a consistent pattern across all the detrending methods that the decline in the correlation between TFP and output is clearly less than that between labor productivity and output. As will be discussed further later, this is largely due to the steeper decline in the variance of TFP relative to LP growth rates, more than offsetting an increase in the correlation between capital deepening and output over time, contributing to the deeper decline in the LP-output correlation.

The magnitude of the decline in the TFP-output correlation is fairly comparable across different detrending methods (specifically from the bandpass, the HP, and the CF filters), with the bandpass-filtered data exhibiting the largest point estimate of the decline.[15] This pattern of robustness to detrending methods is similar to that found for the LP-output correlation. At the same time, we find that

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[14] The quarterly data of TFP and utilization-adjusted TFP for total business sector are compiled by John Fernald and made available online at http://www.frbsf.org/economics/economists/jfernald/quarterly_tfp.xls. The version used here are downloaded on Aug. 24, 2012. See Fernald (2012) for more details about the data, which differ in minor ways from the official BLS data for private business sector.

[15] This ranking in terms of the decline in the points estimates is the same as that from the same comparison (not reported for brevity but available upon request) using the official BLS multifactor productivity data, which are only available at the annual frequency.

formal structural tests a la Bai and Perron (2003) and Elliot and Muller (2006), which explicitly account for the uncertainty in the timing of the break(s), cannot reject the null that there has not been a significant change in the relationship between TFP and output.

It is interesting to note that, unlike for the LP-output correlation, shortening the sample period seems to make a more perceptible difference for the change in the TFP-output correlation since the mid 1980s. Table 3a reports the same correlation statistics as Table 3 but for 1960 to 2007, the sample period when industry data are available. We notice that the reduction in correlation is more pronounced in quarterly data over this shorter period, although the gap may not be significant.

2.3 Cyclicality of Utilization-Adjusted Total Factor Productivity

Last we discuss the evidence for any change in the cyclical comovement between utilization-adjusted TFP and private business output at the quarterly frequency. This is an attempt to gauge to what extent there has been a change in the cyclical property of "true" technology shocks. As Basu (1996), Basu and Fernald (2001) and Basu, Fernald and Kimball (2006) make clear, the standard TFP (i.e., Solow residual) is not a correct measure of the true change in technology because it also contains the impact of measured fluctuations in resource utilization (that is, labor effort and capital utilization) and non-constant returns to scale. As reviewed in Basu and Fernald (2001), these other influences can explain the bulk of the procyclicality of TFP and LP. Adjusting TFP for variable resource utilization thus provides a more accurate measure of the true change in technology.[16] Basu and Fernald (2002) further point out that, at the aggregate level, productivity is also influenced by reallocation of resource across firms facing different prices for inputs and output.

We again apply the same set of methods for trend-cycle decomposition as used above. The results are reported in Table 4. Comparing these with statistics in the top panel reveals that there has been much less change in the cyclical relationship between output and technology shocks than for the cyclical correlation between output and LP and TFP. In fact, other than using the HP-filtered series, there is essentially no change in this correlation based on quarterly data, and only slightly more of a decline in annual data. This suggests that the modest fall in the correlation between TFP and output is largely due to changes in the cyclical property of resource utilization. We will discuss later what this implies about

[16] John Fernald's quarterly TFP data are not adjusted for possible increasing returns to scale. This is, however, generally not a concern for U.S. aggregate data, as Basu and Fernald (1997) and Rotemberg and Woodford (1995) have shown.

the proposed mechanisms for the diminished output-productivity correlation.

Interestingly, shortening the sample period to 1960 to 2007, estimates for which are listed in Table 4a, makes the most difference for the cyclical correlation between technology (that is, utilization-adjusted TFP) and output. Comparing Table 4a and Table 4 shows that the decline in correlation is nearly as large as for the TFP-output correlation over the shorter time series. Moreover, comparing between the TFP-output and technology-output correlation for the two subperiods indicates that adjusting for utilization makes more of a difference for the pre-1960 data – resulting in a much lower correlation between output and true technology.

In summary, evidence based on aggregate data suggest that the cyclical fluctuation of labor productivity has become less correlated with output, significantly so when one can justify ignoring the uncertainty regarding the timing of the change in the relationship, for example because it can be identified with a known event with clear consequences. By comparison, the correlation between TFP and output has not declined nearly as much. Furthermore, the correlation between utilization-adjusted TFP (which best approximates the true technology) and output has not changed at all. We next discuss what theory suggests about plausible explanations for these "stylized facts."

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

This section discusses briefly the basic understanding of the cyclical relationship among productivity, inputs and output according to leading theories of business cycle, and what they imply about the potential mechanisms that can cause the comovements among these variables to change. We will pay special attention to the role of possible time variations in measurement errors in the observed variables. For heuristic purpose, we distinguish between a case where all variables are measured precisely and a (more realistic) case where one or more of the variables are measured with errors.

3.1 The Cyclical Relationship without Measurement Errors

We first discuss the cyclical comovements among output, inputs and productivity when all of them are assumed to be observed without errors. In fact, for growth accounting, all that is needed is that the degree of measurement errors is not time-varying, since a constant error is differenced out in growth rate calculations.[17] We start with the definition of labor productivity: the amount of output per hour of all

[17] The same applies to data detrended with filters other than first difference, such as Hodrick-Prescott (HP) or band-pass, since these filters when applied to integrated data effects a first differencing.

workers. If we measure output using value added (VA), which is the relevant output measure for the economy as a whole, then the growth rate of LP, denoted da, can be expressed as:[18]

$$\mathrm{d}a = \mathrm{d}v - \mathrm{d}h = \mathrm{d}v - (\mathrm{d}l - \mathrm{d}lq). \tag{1}$$

dv, dh, dl and dlq are the growth rates of VA, total hours, total labor services and labor quality, respectively. [19] The second equal sign uses the standard definition of labor input: input of labor services is total hours scaled by labor quality. In growth rates, this means that labor input equals the sum of total hours and labor quality, and so dh = dl – dlq.

LP growth can be decomposed further into TFP growth and capital deepening. The growth rate of VA-based TFP, denoted dt, is defined as output growth net of the growth in primary inputs capital and labor:[20]

$$\mathrm{d}t = \mathrm{d}v - (s_K^V \mathrm{d}k + s_L^V \mathrm{d}l) \equiv \mathrm{d}v - \mathrm{d}x^V, \tag{2}$$

where dk and dx^V are growth rates of capital services and primary inputs, respectively. s_L^V and s_K^V are shares of labor and capital income in nominal VA, respectively. dt is also called the Solow residual because it is the residual output growth after accounting for input growth. Inserting (2) into (1), we obtain the following expanded expression for LP growth:

$$\mathrm{d}a = \mathrm{d}v - (\mathrm{d}l - \mathrm{d}lq) = \mathrm{d}v - \mathrm{d}x^V + s_K^V\left(\mathrm{d}k - \mathrm{d}l\right) + \mathrm{d}lq = \mathrm{d}t + s_K^V\left(\mathrm{d}k - \mathrm{d}l\right) + \mathrm{d}lq. \tag{3}$$

Equation (3) spells the familiar relationship that (in growth rates) labor productivity equals TFP plus capital deepening (dk – dl) weighted by capital's share in value added, plus labor quality.

We can now derive the relationship between da and dt in terms of variance. It depends on the relative magnitude of the variance of (dk - dl) and its covariance with dt:[21]

$$\mathrm{var}(\mathrm{d}a) = \mathrm{var}(\mathrm{d}t) + \left(s_K^V\right)^2 \mathrm{var}\left(\mathrm{d}k - \mathrm{d}l\right) + 2 s_K^V \mathrm{cov}\left(\mathrm{d}t, \mathrm{d}k - \mathrm{d}l\right).$$

In data, the variance of da is generally somewhat smaller than that of dt. This implies that the covariance term needs to be sufficiently negative to more than offset the positive term of the variance of (dk - dl) scaled by $\left(s_K^V\right)^2$. As we will show, the negative covariance between TFP and capital deepening is driven

[18] All variables are measured at a point in time, but we omit the time subscripts for clarity.

[19] In general, the lower case letters stand for the logrithm of the corresponding capital letters, and d stands for difference. Log differences represent growth rates.

[20] Note that TFP (growth) can also be defined based on gross output, which can be seen in derivations in Appendix I. It equals VA-based TFP multiplied by the VA share.

[21] For clarity, we ignore labor quality in all the following derivations because its changes are much smaller compared to those of the other items, especially at business cycle frequency.

by the positive comovement between hours and input utilization: when hours growth slows, utilization also falls. Thus capital intensity rises while TFP falls.

Now we derive the covariance and correlation between aggregate output and these measures of productivity, all measured in growth rates. The correlation that has garnered the most attention in previous studies is between output and LP, both measured on a value added basis. Equation (3) and the bilinear nature of covariance imply that the LP-VA covariance, denoted $\sigma(\mathrm{d}a, \mathrm{d}v)$, can be simply expressed as the sum of covariances of its two components (that is, TFP $\mathrm{d}t$ and capital deepening $\mathrm{d}k - \mathrm{d}l$) with VA. By comparison, the decomposition using (3) of the LP-VA correlation, denoted $\rho(\mathrm{d}a, \mathrm{d}v)$, is a weighted sum of correlations between components of $\mathrm{d}a$ and $\mathrm{d}v$, with the volatility ratio of each corresponding component to $\mathrm{d}a$ as the weight:

$$\rho(\mathrm{d}a, \mathrm{d}v) = \rho(\mathrm{d}t, \mathrm{d}v)\frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}a)} + s_K^V \rho\left[\left(\mathrm{d}k - \mathrm{d}l\right), \mathrm{d}v\right]\frac{\sigma(\mathrm{d}k - \mathrm{d}l)}{\sigma(\mathrm{d}a)}, \tag{4}$$

where $\sigma(.)$ is the standard deviation (also called volatility) of a variable.

Hence, the difference between LP and TFP in terms of their correlation with VA (that is, $\rho(\mathrm{d}a, \mathrm{d}v) - \rho(\mathrm{d}t, \mathrm{d}v)$) stems from not only the difference between the corresponding covariances, which involves only the covariance between capital deepening and VA (weighted by s_K^V), but also the difference between their volatilities. There is an intuitive relationship between LP-VA and TFP-VA correlations in percentage terms, assuming they have the same sign: their difference equals the difference between the two corresponding covariances net of the difference between LP's and TFP's volatility:[22]

$$\%\Delta\rho_{LP-TFP} = \ln\left[\left|\rho(\mathrm{d}a, \mathrm{d}v)\right|\right] - \ln\left[\left|\rho(\mathrm{d}t, \mathrm{d}v)\right|\right] = \left\{\ln\left[\left|\sigma(\mathrm{d}a, \mathrm{d}v)\right|\right] - \ln\left[\left|\sigma(\mathrm{d}t, \mathrm{d}v)\right|\right]\right\} - \left\{\ln\left[\sigma(\mathrm{d}a)\right] - \ln\left[\sigma(\mathrm{d}t)\right]\right\}. \tag{5}$$

ln(.) denotes the natural logarithm of a variable.

Equation (4) then implies that changes in the LP-VA correlation $\rho(\mathrm{d}a, \mathrm{d}v)$ can stem from not only changes in correlations between LP components and VA but also changes in the relative volatility of each component. For example, TFP can contribute to a reduction in $\rho(\mathrm{d}a, \mathrm{d}v)$ either because its correlation with VA declines or its volatility falls relative to LP's volatility, or both. Applying a similar approach, we can approximate the percentage change in a correlation as follows, assuming the correlation is initially positive but can fall to negative subsequently:

$$\frac{\Delta\rho(x,y)}{\rho_0(x,y)} \approx \frac{\Delta\,\mathrm{cov}(x,y)}{\mathrm{cov}_0(x,y)} - \frac{\Delta\sigma(x)}{\sigma_0(x)} - \frac{\Delta\sigma(y)}{\sigma_0(y)}.$$

[22] The sign of this difference should be reversed if the two correlations are both negative.

This then implies that the difference, in terms of percentage change over time, between LP-VA and TFP-VA correlations can be expressed as the difference between the two corresponding covariances net of the difference between LP's and TFP's volatility:

$$\frac{\Delta\rho(\mathrm{d}a,\mathrm{d}v)}{\rho_0(\mathrm{d}a,\mathrm{d}v)}-\frac{\Delta\rho(\mathrm{d}t,\mathrm{d}v)}{\rho_0(\mathrm{d}t,\mathrm{d}v)}\approx\left[\frac{\Delta\operatorname{cov}(\mathrm{d}a,\mathrm{d}v)}{\operatorname{cov}_0(\mathrm{d}a,\mathrm{d}v)}-\frac{\Delta\operatorname{cov}(\mathrm{d}t,\mathrm{d}v)}{\operatorname{cov}_0(\mathrm{d}t,\mathrm{d}v)}\right]-\left[\frac{\Delta\sigma(\mathrm{d}a)}{\sigma_0(\mathrm{d}a)}-\frac{\Delta\sigma(\mathrm{d}t)}{\sigma_0(\mathrm{d}t)}\right]. \tag{6}$$

The changes in covariances and variances in this equation are implied by (1) as follows:[23]

$$\Delta\operatorname{cov}(\mathrm{d}a,\mathrm{d}v)=\Delta\operatorname{cov}(\mathrm{d}t,\mathrm{d}v)+2s_K^V\Delta\operatorname{cov}\left(\mathrm{d}k-\mathrm{d}l,\mathrm{d}v\right), \tag{7}$$

$$\Delta\operatorname{var}(\mathrm{d}a)=\Delta\operatorname{var}(\mathrm{d}t)+\left(s_K^V\right)^2\Delta\operatorname{var}\left(\mathrm{d}k-\mathrm{d}l\right)+2s_K^V\Delta\operatorname{cov}\left(\mathrm{d}t,\mathrm{d}k-\mathrm{d}l\right). \tag{8}$$

We now discuss the relationship between LP-VA and TFP-VA correlations in data, assuming for now as if they were observed without errors. Overall, the LP-VA correlation has fallen more than the TFP-VA correlation, that is, the left hand side of equation (6) is negative, when we compare the two subperiods 1984 to 2007 versus 1960 to 1983. This is true in both level and percentage terms. In addition, this pattern holds for bandpass-filtered quarterly and annual data, as well as for the fourth-difference of quarterly data or the first-difference of annual data. Not surprisingly, including the recent crisis and deep recession from 2008 to 2011 in the later period almost invariably narrows the changes — makes them less negative — between the two periods, although most changes remain solidly negative, especially for the LP-VA correlation.

In terms of the *percentage* change in comovement with VA between the two subperiods, the decline is greater for LP than for TFP, especially when the comovement is measured using correlation instead of covariance. This is because TFP's volatility has in fact fallen more than LP's volatility over time (by comparing Tables 1 and 2). Specifically, terms in the first square bracket on the right hand side of (6) (equal to the relative change between the two covariance terms) yield a negative value while those in the second bracket (equal to the relative change between LP's and TFP's volatility) net out positive.

Interestingly, even though cov(dt, dv) has fallen less than cov(da, dv) in percentage terms, the relationship is in fact reversed in levels. This is because cov(dt, dv) starts from a much higher baseline (that is, value before 1984) than cov(da, dv). According to (7), in levels, cov(dt, dv) has declined more over time than cov(da, dv) because cov(dv, dk - dl) has increased—turned less negative. In fact, capital deepening and VA has become nearly uncorrelated in recent decades. One likely underlying force is changes in the composition of capital over time: the share of capital related to information and

[23] To be precise, the total derivative should take account of changes over time in the capital share, which are ignored here because this share has seen little change on average over the two subperiods.

communication technology (ICT) has grown steadily since the late 1970s and rapidly during the late 1990s. It is well documented that ICT capital features much high depreciation rates than non-ICT capital. Hence, capital stock can shrink more quickly along with employee layoffs in the latter subperiod, leaving capital deepening (dk - dl) less correlated with output growth dv.

Regarding the volatility of LP (da) and TFP growth (dt), σ(da) has declined less than σ(dt) because both σ(dk - dl) and cov(dk - dl, dt) have risen. The latter has become less negative, suggesting that variations in utilization may have become less correlated with hours. To the extent that the relationship between utilization and weekly hours has remained more or less stable over time, then utilization, approximated by weekly hours, has become less variable in the latter subperiod. Its volatility, however, has declined less than that of employment and even less than that of output. This is likely the result of lower persistence in output growth, as will be shown later. Changes in capital composition discussed above may have contributed to the high covariance as well.

If we measure cyclicality using the comovement with input instead of output growth, then it is obvious that the covariance with output exceeds that with inputs because, using TFP for example, $\operatorname{cov}(\mathrm{d}t, \mathrm{d}x^V) = \operatorname{cov}(\mathrm{d}t, \mathrm{d}v) - \operatorname{var}(\mathrm{d}t)$. This relationship turns out to hold also in terms of correlation, that is, $\rho(\mathrm{d}t, \mathrm{d}x^V) \le \rho(\mathrm{d}t, \mathrm{d}v)$. This can be derived using the definition $\mathrm{d}v = \mathrm{d}x^V + \mathrm{d}t$ and the implied inequality $\sigma(\mathrm{d}x^V) + \sigma(\mathrm{d}t) \ge \sigma(\mathrm{d}v)$ since $\rho(\mathrm{d}t, \mathrm{d}x^V) \le 1$:

$$\rho(\mathrm{d}t, \mathrm{d}v) = \rho(\mathrm{d}t, \mathrm{d}x^V)\frac{\sigma(\mathrm{d}x^V)}{\sigma(\mathrm{d}v)} + \frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)} \ge \rho(\mathrm{d}t, \mathrm{d}x^V)\left[\frac{\sigma(\mathrm{d}x^V) + \sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)}\right] \ge \rho(\mathrm{d}t, \mathrm{d}x^V)\,. \tag{9}$$

Therefore, TFP's correlation with output always exceeds its correlation with input.

In terms of the relative change over time, it is obvious that any difference in terms of covariance must be due to changes in the variance of TFP growth. If TFP becomes less volatile, then its covariance with output must decline more than its covariance with input. The relationship between the two correlations, however, is less clear cut since

$$\Delta\rho(\mathrm{d}t, \mathrm{d}v) - \Delta\rho(\mathrm{d}t, \mathrm{d}x^V) \approx \Delta\rho(\mathrm{d}t, \mathrm{d}x^V)\left[\frac{\sigma_0(\mathrm{d}x^V)}{\sigma_0(\mathrm{d}v)} - 1\right] + \rho_0(\mathrm{d}t, \mathrm{d}x^V)\Delta\left[\frac{\sigma(\mathrm{d}x^V)}{\sigma(\mathrm{d}v)}\right] + \Delta\left[\frac{\sigma(\mathrm{d}t)}{\sigma(\mathrm{d}v)}\right]. \tag{10}$$

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 being 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. This exactly describes the empirical situation at the aggregate level. In fact, TFP has become negatively correlated with input in the post-84 period.

3.2 Cyclical Relationships with Systematic Measurement Errors

It is unrealistic to regard all variables as precisely estimated or, more pertinently, that the degree of measurement errors does not vary *systematically* over the business cycle. Note that these are not classical measurement errors in that they are (positively) correlated with observed variables and thus fluctuate cyclically. Basu and Kimball (1997) show that cost minimization implies firms would want to adjust inputs along all the margins, observed as well as unobserved. For instance, when firms are boosting their payroll and raising weekly hours in an economic boom, they should also demand more effort from workers, which is unobserved. We next discuss what are the implications of systematic (cyclical) noise in the observed growth rates or detrended data. The main result is that changes in the observed cyclical relationship can be entirely due to changes in the cyclical property and relative magnitude of unmeasured inputs.

We focus on measurement errors in inputs, because, as will be shown, correcting for unmeasured inputs is sufficient to explain the reduction in TFP's correlation with input as well as output growth. Nevertheless, in Appendix II, we derive how TFP's cyclicality can be observed to change allowing for measurement errors in both inputs and output. It demonstrates that changes in the cyclical property of unmeasured inputs or output can result in less procyclical TFP. To the extent taking account of unmeasured inputs can explain the change in TFP's cyclicality without any change in true technology's cyclicality, there is little need for changes in the cyclical behavior of unmeasured output.

We adopt the method developed in Basu and Kimball (1997) and applied in BFK (2006) to adjust for unmeasured fluctuations in input utilization, encompassing elements such as time-varying labor effort and capital workweek. Following BFK (2006), we express these corrections in terms of the relationship between TFP ($\mathrm{d}t$) and true technology ($\mathrm{d}z$, also referred to as utilization-adjusted or purified TFP) growth. As detailed in Appendix I, at a firm or industry level, TFP includes not only technology but

also contribution from unmeasured inputs along with measured input due to non-constant returns to scale:

$$\mathrm{d}t_{it}=\left(\mu_i-1\right)\mathrm{d}x_{it}^V+\mu_i\mathrm{d}u_{it}^V+\left(\mu_i-1\right)\frac{s_{Mi}}{1-s_{Mi}}\mathrm{d}m_{it}+\mathrm{d}z_{it}^V=\left(\mu_i-1\right)\frac{\mathrm{d}x_{it}}{1-s_{Mi}}+\mu_i\mathrm{d}u_{it}^V+\mathrm{d}z_{it}^V. \qquad (11)$$

$\mathrm{d}x_{it}=s_{Li}\mathrm{d}l_{it}+s_{Ki}\mathrm{d}k_{it}+s_{Mi}\mathrm{d}m_{it}$ is the revenue-weighted growth of all inputs, that is, growth rates of 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 do not necessarily sum to one if there is pure profit. $\mathrm{d}x^V=\left(s_{Li}\mathrm{d}l+s_{Ki}\mathrm{d}k\right)/\left(1-s_{Mi}\right)$ is the growth rate of primary inputs, measured on a VA basis. μ denotes the markup on gross output, which equals returns to scale with zero profit. $\mathrm{d}u^V$ denotes the composite labor and capital utilization term, measured on a VA basis. $\mathrm{d}z^V$ is the true technology shock measured on a VA basis.

Basu and Kimball (1997) show that under fairly general conditions—chiefly cost minimization—the unobserved labor effort and capital utilization is a monotonically increasing function of the observed intensive margin of average hours per worker (over a given period such as a week or a year). A first-order approximation in growth rate yields: $\mathrm{d}u=\left(\zeta/\mu\right)\mathrm{d}h$, where ζ is the elasticity of input utilization in general with respect to hours per worker, and μ is the gross-output markup.[24] In Appendix III, we extends their analysis to show that the conclusion of using weighted average hours as the observed margin to proxy for the unobserved input remains valid even in a case where there is unmeasured output of investment produced in-house. The average hours, however, cannot serve as a proxy for the unobserved output without further assumptions.

Equation (11) makes clear that TFP is not a correct measure of true technology as long as there is unmeasured input variations. Moreover, if there is a markup (for example due to non-constant returns to scale), that is, $\mu \neq 1$, then TFP also includes the contribution from inputs when the scale of production changes. TFP's correlation with primary input growth $\mathrm{d}x^V$ thus can be decomposed as follows (with *it* subscripts omitted for clarity):

$$\rho\left(\mathrm{d}t,\mathrm{d}x^V\right)=\frac{\mu_i-1}{1-s_{Mi}}\frac{\sigma(\mathrm{d}x)}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}x,\mathrm{d}x^V\right)+\mu_i\frac{\sigma(\mathrm{d}u^V)}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}u^V,\mathrm{d}x^V\right)+\frac{\sigma(\mathrm{d}z^V)}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}z^V,\mathrm{d}x^V\right). \qquad (12)$$

Since firms tend to adjust various margins of input in the same direction, the first two correlations tend to be fairly positive. This implies that TFP can be quite positively correlated with inputs (that is, being procyclical) without large positive, or even with negative, correlation between technology

24 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, wage premium paid to labor because of a longer work week.

and inputs. This is indeed the pattern found in BFK (2006), and confirmed here, as will be shown later. Equation (11) then implies the following expression for changes in the TFP-input correlation (analogous to equation (10)):

$$\Delta\rho\left(\mathrm{d}t,\mathrm{d}x^V\right)=\frac{\mu_i-1}{1-s_{Mi}}\Delta\left[\frac{\sigma(\mathrm{d}x)}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}x,\mathrm{d}x^V\right)\right]+\mu_i\Delta\left[\frac{\sigma(\mathrm{d}u^V)}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}u^V,\mathrm{d}x^V\right)\right]+\Delta\left[\frac{\sigma(\mathrm{d}z^V)}{\sigma(\mathrm{d}t)}\rho\left(\mathrm{d}z^V,\mathrm{d}x^V\right)\right]. \quad (13)$$

To illustrate the combination of forces that can reduce the TFP-input correlation, we set markup μ_i to 1 and eliminate the first term. Then the change in TFP-input correlation becomes:

$$\begin{aligned}\Delta\rho\left(\mathrm{d}t,\mathrm{d}x^V\right)=\mu_i&\left\{\Delta\left[\frac{\sigma(\mathrm{d}u^V)}{\sigma(\mathrm{d}t)}\right]\rho_0\left(\mathrm{d}u^V,\mathrm{d}x^V\right)+\frac{\sigma_0(\mathrm{d}u^V)}{\sigma_0(\mathrm{d}t)}\Delta\rho\left(\mathrm{d}u^V,\mathrm{d}x^V\right)\right\}\\&+\Delta\left[\frac{\sigma(\mathrm{d}z^V)}{\sigma(\mathrm{d}t)}\right]\rho_0\left(\mathrm{d}z^V,\mathrm{d}x^V\right)+\frac{\sigma_0(\mathrm{d}z^V)}{\sigma_0(\mathrm{d}t)}\Delta\rho\left(\mathrm{d}z^V,\mathrm{d}x^V\right).\end{aligned} \quad (14)$$

Obviously, the TFP-input correlation, $\rho(\mathrm{d}t, \mathrm{d}x^V)$, falls if either $\rho(\mathrm{d}u^V, \mathrm{d}x^V)$ or $\rho(\mathrm{d}z^V, \mathrm{d}x^V)$ is lower. But more importantly, equation (14) shows that $\rho(\mathrm{d}t, \mathrm{d}x^V)$ could fall even if neither correlation on the right hand side changed: TFP could still become less correlated with input if the volatility of technology rose relative to that of TFP to yield a sufficiently negative third term, since technology and input were negatively correlated before the mid 1980s and have remained so. $\sigma(\mathrm{d}z^V)$ can rise relative to $\sigma(\mathrm{d}t)$ if the covariance between unmeasured input utilization ($\mathrm{d}u^V$) and $\mathrm{d}z^V$ falls, since equation (11) shows that $\mathrm{d}t$ is simply the sum of $\mathrm{d}z^V$ and $\mathrm{d}u^V$ when $\mu_i = 1$. Hence, $\sigma^2(\mathrm{d}t) = \sigma^2(\mathrm{d}u^V) + \sigma^2(\mathrm{d}z^V) + 2\mathrm{cov}(\mathrm{d}u^V, \mathrm{d}z^V)$. For given variances of $\mathrm{d}z^V$ and $\mathrm{d}u^V$, the variance of $\mathrm{d}t$, $\sigma^2(\mathrm{d}t)$, rises and falls with $\mathrm{cov}(\mathrm{d}u^V, \mathrm{d}z^V)$. The volatility ratio between $\mathrm{d}z^V$ ($\mathrm{d}u^V$) and $\mathrm{d}t$ thus rises as $\mathrm{cov}(\mathrm{d}u^V, \mathrm{d}z^V)$ falls. Note that the increase in $\sigma(\mathrm{d}u^V)$ relative to $\sigma(\mathrm{d}t)$ offsets to some extent the effect of the relative increase in $\sigma(\mathrm{d}z^V)$, since all margins of inputs generally move in the same direction. But if the net effect is dominated by the latter, then TFP will become less correlated with inputs.

In words, TFP can become less procyclical if the unmeasured inputs in fact respond more negatively to technology shocks. As we will show, this turns out to be the main empirical reason why TFP has become less correlated with input growth since the mid 1980s. At the aggregate level, growth volatility of technology has actually risen because of somewhat greater correlation across industries. This pattern can arise if technology shocks have somehow become less persistent, since the unmeasured input contribution is tied to the intensive margin of labor input. The logic is analogous to that shown in Ramey and Vine (2006): firms adjust the intensive margin more when the shock process becomes less persistent since mainly or only the extensive margin is subject to adjustment costs. As we will show, however, there is more evidence for greater than for less persistence in technology shocks. We will discuss how these

seemingly contradictory patterns can be reconciled in the context of the forces for less procyclical productivity.

With this framework in mind, we now turn to discuss the mechanisms that have been proposed to explain the decline or even disappearance of the procyclicality of LP based on observed data.

3.3 Potential Mechanisms for the Diminished Procyclicality of Labor Productivity

This section discusses two primary proposals examined in previous studies to explain the likely reasons for a decline in the correlation between LP and VA since the mid 1980s. We preface the discussion by noting that both hypotheses rely on mismeasurement and its change over time to explain the phenomenon concerned. One proposal considers the impact of diminishing mismeasurement of input while the other advocates increasing mismeasurement of output.

3.3.1 Improvements in Labor Market Flexibility

Gali and van Rens (2010) propose that the main reason for the disappearance of the procyclicality of labor productivity is that various reforms of labor market institutions have made it more flexible over time so that firms are now able to adjust along the extensive — employment — margin at a lower cost. All else being equal, firms would respond by making more of the labor input adjustment via the employment margin, relative to the hours or effort margin, than they did previously. In other words, there would be less labor hoarding. Greater flexibility in the labor market is an actual change to the underlying structure of the economy, but it has impact on the measured cyclicality of productivity only because we generally cannot precisely measure the true quantity of inputs. Some elements, such as labor effort and capital utilization, are poorly measured, if at all.

More importantly for growth accounting purpose, the degree of mismeasurement varies with the true level of effort or utilization, which almost surely fluctuates over the business cycle. The most plausible pattern of cyclical variations in the true input of effort or usage intensity is that they rise when the economy is expanding and fall when it is contracting. Basu and Kimball (1997) derive such a relationship under the basic assumption of cost minimization and fairly general conditions for the production technology. This then introduces a time-varying wedge between the measured and true input that alters the observed degree of comovement between productivity and output -- increases it under most common assumptions.

If structural changes cause the effort level to fluctuate less over the business cycle while holding all else equal, it will reduce the variation in the degree of input mismeasurement. As a result, the

observed correlation between productivity and input and in turn output will fall.[25] This is consistent with the above finding in Section 2 that the cyclical correlation between output and LP as well as TFP has changed little for the first-differenced quarterly data. The argument is that any increased flexibility for adjusting employment is likely to be a much less relevant force at such a high frequency.

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). It is clearly inconsistent with the empirical evidence that the correlation between input and TFP and utilization-adjusted TFP has turned negative since the mid 1980s. Gali and van Rens (2010) thus introduce a preference shock, which leads to a negative correlation between productivity and inputs because of decreasing returns to scale to labor input. The two shocks combined are then calibrated to yield a negative unconditional correlation between LP and inputs.

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 a model with price rigidity or imperfect common knowledge, as discussed in BFK (2006). As we will show, patterns emerging from industry data suggest a convergence since the mid 1980s toward a baseline case of negative correlation between technology shocks and inputs. This is also consistent with the above finding in Section 2 that the correlation between utilization-adjusted TFP and output has remained essentially unchanged for the full time period of 1950 to 2009.

In addition to the diminished procyclicality of productivity, the hypothesis by Gali and van Rens (2010) also offers the following two implications concerning the relative volatility of employment and real wage versus output. They show that both employment and real wage will become more volatile relative to real output as the labor market becomes more flexible so that firms choose to adjust employment more and at the same time there is a narrower range within which wages can remain unchanged and yet to sustain a bargaining equilibrium.

As the empirical results reported later will show, input volatility has indeed fallen relative to output volatility since the 1984, which can be construed as evidence for more flexible factor markets in general. At the same time, however, the unconditional volatility of employment has fallen more than that of average hours for many industries and the private economy as a whole. To still be consistent with the

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

conjecture of more flexible labor institutions, we would need either demand or technology, or both, shocks to become less persistent, which induces firms to use more of the intensive margin to adjust inputs, as shown in Ramey and Vine (2006). We will show later in the empirical section that there is some evidence that industries experiencing more a decline in output persistence also exhibits more an increase in the unconditional volatility of average hours relative to that of employment.

3.3.2 Increased Importance of Intangible Investment

In a number of papers, McGratten and Prescott (2007, 2012) advocate an explanation for the diminished procyclicality of labor productivity based on an increase in the relative size of private firms' activities that are devoted to creating intangible capital as compared to operations devoted to producing market output. They emphasize that their definition of intangible investment is rather broad to include a wide range of activities that can be regarded as some form research and development (R&D) aimed at improving processes or developing new products, all of which should result in greater earnings ability in the future. McGratten and Prescott (2007, 2012) offer some indicative statistics for the amount of R&D carried out by private businesses, and argue that data show there has been a substantial rise in the relative size of R&D activities vis-à-vis sales revenue of market output.

The impact of changing importance of unmeasured production of own capital on the cyclicality of productivity can be seen through derivations in Appendix II (equation (17)). In particular, it is shown that unmeasured output needs to start small relative to measured output, in which case faster growth in the former will imply falling procyclicality of LP. Otherwise, if the former's share starts high, its faster growth will in fact lead to more procyclical LP.

McGratten and Prescott (2007, 2012) do not, however, explicitly examine the reasons for the timing of the increase in intangible investment, even though it would seem a central question. Why have firms boosted their engagement in those activities that enhance future earnings power but do not generate marketable output currently 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 communicate technology (ICT). It seems reasonable to date the first wave of widespread adoption of ICT with the IBM personal computers in the early 1980s.

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 those adoptors. In order to take full advantage of the new technology, however, firms that adopt ICT in their operation have to make complementary investment in order to transform and optimize the production process to realize the full

potential of the new technology. In the case of ICT, a number of studies have argued 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 and adding to new (intangible) capital.

Several earlier papers have made the connection between unmeasured investment and measured productivity growth fluctuations over time. For example, Basu, Fernald and Shapiro (2001) show that the standard capital adjustment cost may have had a nontrivial impact on the pattern of measured productivity growth during the late 1990s and early 2000s, when investment went from booming to slumping after the internet bubble burst. In terms of the distortionary impact on measured output and hence productivity, 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 can take the form of foregone market output. To the extent firms optimize investment by equalizing the marginal payoff on different types of capital, intangible investment, like measured investment, is likely to be procyclical. To be consistent with the lack of a change in the cyclicality of productivity at the quarterly frequency, however, we need adjustments of intangible investment to be made at a lower frequency so that the high-frequency cyclicality of productivity is not affected by increased importance of intangible investment.

Since investment adds to the capital stock, intangible investment leads to an opposite distortion to measured productivity intertemporally in that true capital stock and hence capital services are understated.[26] This is recognized in Basu, Fernald, Oulton and Srinivasan (BFOS, 2004). In terms of the impact on measured business cycle comovements between productivity and output, the model in BFOS (2004) suggests that it is dominated by the magnitude of cyclical fluctuations in unobserved intangible investment. Cyclical variations in the unmeasured contribution from the resulting intangible capital is minor by comparison.

In short, the evidence discussed thus far based on aggregate data seems to favor the explanation based on changes in labor market flexibility, compared with the one based on growing importance of unmeasured investment in intangible capital. Our subsequent analysis using industry data will also show that it is difficult to explain the change after 1984 in labor input's reaction to technology shocks with the model based on unmeasured intangible investment. We next turn to disaggregated data at the industry level to further explore evidence for these proposed explanations for the vanishing procyclical of productivity.

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

IV. Evidence based on Industry Data

The advantage of industry data over aggregate data is that the former enable us to utilize cross-industry heterogeneity in characteristics that should influence how firms in an industry adjust inputs and output and thus the degree of mismeasurement in observed productivity-output correlation. Moreover, 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) is borne out in the cross section. Furthermore, industry data enable us to account for contribution from input variations to measured productivity and uncover the true technology term. We can thus examine to what extent the change in the cyclicality of productivity is due to changes in the cyclical property of technology or the input-related components. Last, it has been shown, for example in Basu and Fernald (2002), 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 attributed more to the average change at the industry level or to the terms related to resource allocations 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.

We note that all the analyses using these industry data focus on only what we term the nonfarm private industries, 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 more driven by shocks emanating from nature. The public sector's output is so poorly measured that by definition it has zero productivity growth.

4.1 Data

We use three sources of data for our micro level analysis. The primary source is the industry data set compiled by Dale Jorgenson and his colleagues and made available to the research community.[27] The

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

version used here has been updated from a SIC-based industry classification system to a NAICS-based system, and the data updated to 2007.[28] "Total industries" in this dataset includes not only private industries but also government enterprises and public administration. Table A.1 in the appendix lists all the 31 industries covered in this dataset, plus the 7 sub-aggregates, which are italicized. Table A.2 reports the summary statistics of input and output growth rates and factor shares, with the 27 private nonfarm industries in Panel A and all 30 industries (excluding private households with employed persons) in Panel B. The primary advantage of this data set is that it covers a long time series, starting from 1947, whereas other NAICS-based industry data sets, such as those compiled by the BEA or the BLS, mostly start in 1987. 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 industries' characteristics such as the durability of their outputs, which measure their demand sensitivity to aggregate shocks and hence industry-specific demand volatility. These data are compiled by Bils, Klenow and Malin (2012).

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

4.2 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, using three different filters: HP (with the standard parameter for annual data), Christiano-Fitzgerald bandpass (with cyclical component defined as between two to eight years) and first-difference (FD, equivalent to annual growth rate). Figures 2a and 2b provide scatterplots of changes in the correlation between LP and primary input growth after versus before 1984 by industry based on different trend-cycle filters; Table 5 summarizes the pattern using the cross-industry correlation in these changes, as well as changes in the LP-VA correlation.[29] 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 TFP-input correlation,

[28] For more details of the data, see Jorgenson, Ho and Samuels (2012).

[29] 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 that small differences in value lead to more pronounced differences in ranking.

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.

4.3 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. The main objective is to ascertain if the cross-industry pattern is sufficiently similar between the two measures to justify focusing our attention on TFP in all subsequent analyses, which is more naturally decomposed into the true technology term and terms related to input utilization. We again use the cross-industry correlation to summarize the degree of similarity between the measures. Table 6 reports the cross-industry relationship between LP and TFP in terms of the change in their correlation with VA and primary inputs after 1984. It is clear that the change in cyclicality at the industry level is extremely similar using either productivity measure, and regardless whether cyclicality is measured vis-à-vis VA or primary inputs. We therefore will focus on analyzing the post-1984 change in the cyclicality of TFP in all subsequent analyses.

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

We first examine a simple decomposition of the correlation between 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:

$$\rho\left(\mathrm{d}t,\mathrm{d}x^V\right)=\rho\left(\sum\nolimits_i w_i\mathrm{d}t_{it},\sum\nolimits_i \eta_i\mathrm{d}x_{it}^V\right)$$
$$=\sum_i\frac{w_i\eta_i\sigma\left(\mathrm{d}t_{it}\right)\sigma\left(\mathrm{d}x_{it}^V\right)}{\sigma\left(\mathrm{d}t\right)\sigma\left(\mathrm{d}x^V\right)}\rho\left(\mathrm{d}t_{it},\mathrm{d}x_{it}^V\right)+\sum_i\sum_{j\neq i}\frac{w_i\eta_j\sigma\left(\mathrm{d}t_{it}\right)\sigma\left(\mathrm{d}x_{jt}^V\right)}{\sigma\left(\mathrm{d}t\right)\sigma\left(\mathrm{d}x^V\right)}\rho\left(\mathrm{d}t_{it},\mathrm{d}x_{jt}^V\right).$$

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. Note also that, with N industries, there are $N(N$-1) industry pairs in the cross-industry piece, many more than the

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

To be precise, it should be noted that 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 effect in our computation. As a robustness check, we compare results using time-varying versus time-series-average shares, which are treated as a proxy for steady-state shares, and find little difference.[30]

Table 7 reports the within- versus cross-industry decomposition of aggregate TFP-input correlation. First note that aggregate TFP-input correlation, which is a weighted average across all industry pairs, has fallen more than the unweighted industry average counterpart reported in Table 6, indicating that industries with greater VA weights have experienced more declines in the TFP-input correlation. This is corroborated by the scatterplot of Figures 2a and 2b: most service industries show a decline in LP-input correlation and some are among the most negative.

The table shows that before 1984, within- and cross-industry correlations are about equal and thus contribute proportionally to 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 decline in TFP's correlation with inputs more within each industry than across industries.

4.5 Technology or Unmeasured Input Utilization?

Basu and Fernald (1997, 2001) and BFK (2006) have made a compelling case that the observed procyclicality of productivity is mostly due to cyclical fluctuations in input utilization that are not adequately accounted for. Once adjusted for these terms, the derived true technology term is in fact countercyclical. A natural question thus is how much of the fallen procyclicality is due to changes in the

[30] This latter treatment is consistent with using the steady-state shares in the production function estimation, which is interpreted as a first-order approximation.

cyclical property of the component related to input growth and how much due to changes in the cyclicality of technology shocks. This section explore this decomposition.

First, we carry out the necessary utilization adjustment following the methodology developed in Basu and Kimball (1997) and later applied in BFK (2006). Specifically, we estimate the following first-order approximation to the production function (in growth) for each industry to uncover the markup and technology growth defined based on gross output:

$$\mathrm{d}y_{it} = \mu_i \mathrm{d}x_{it} + \beta_i \mathrm{d}h_{it} + \mathrm{d}z_{it} \,. \tag{15}$$

$\mathrm{d}y_{it}$ and $\mathrm{d}x_{it}$ are the growth rates of gross output and revenue-share-weighted *measured* inputs, which includes labor, capital and intermediate inputs, of industry *i* in period *t*. The input shares used to compute $\mathrm{d}x_{it}$ are time-series averages over the sample years for each industry, which are viewed as a proxy for steady-state values.[31] μ_i in (15) is the markup on gross output. $\mathrm{d}z_{it}$ is the gross-output-augmenting technology, and related to VA-augmenting $\mathrm{d}z_{it}^V$ as follows: $\mathrm{d}z_{it}^V = \mathrm{d}z_i / \left(1 - s_{Mi}\right)$. $\mathrm{d}h_{it}$ is the growth of detrended average hours per worker meant to capture, to a first order, unobserved variations in resource utilization over time. Basu and Kimball (1997) show that, under reasonably weak conditions, it serves to proxy the unobserved cyclical variation in the degree of both labor effort and capital utilization.[32] Specifically, we have the following mapping:

$$\mu_i \mathrm{d}u_{it} = \beta_i \mathrm{d}h_{it} \,. \tag{16}$$

Equation (15) is estimated using LIML 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-size 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): 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

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

[32] 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. There is hardly ever data 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 approximates the degree of labor effort.

in Christiano, Eichenbaum and Evans (2005).[33] The fiscal policy shocks are measured using the growth rate of real government defense spending, as proposed in Hall (1988) and Ramey (1989).[34] Each of these IVs is an annual measure equal to the four-quarter average lagged by two quarters.

The average hours per worker 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.[35] Detrending is necessary because d*h* is meant to proxy cyclical variations in resource utilization.[36] A dummy variable that equals 0 before 1973 and 1 afterward if included to account for the productivity slowdown, although it does not seem significant for most industry groups.

For precision, we estimate (15) 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.[37] We divide the industries into the following four groups (or sectors): i) nondurable 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) all 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 that the slope coefficients are equal across industries within each group.

[33] We have 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, and 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 makes no qualitative difference to our results.
[34] 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 effect changes in output without any change in input.
[35] 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, the average hours per worker first declined through early 1980s and has since recovered partially except for the two large dips during the 1991 and 2001 recessions.
[36] 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.
[37] 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 estimate of decreasing returns to scale are mining and quarrying (C), utilities (E) and financial intermediation. These industries seem all special in some way to render their markup estimates problematic: the output of mining and quarrying is largely commodities, utilities are heavily regulated, while the output of financial intermediation is poorly measured. The utilization coefficient β_i is estimated rather imprecisely for many, especially chemicals, rubber and plastic, all of which feature continuous process production.

To be conservative and limit the impact of input usage to the derived technology series, we use as our baseline case a version of the produce function parameter estimates that constrain μ_i to 1. This amounts to assuming constant returns to scale (CRS) for all industries. This constraint can be justified by the test result that industry-level estimates of μ_i's are all insignificantly different from 1.

Table 8 presents the group estimates of the utilization coefficient β_i while μ_i is restricted to 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 impresisely estimated for construction industry by itself, which is typical of the (unreported) industry-specific estimates of this parameter. As identified by the IVs, the utilization margin makes more contribution to manufacturing TFP (as can be seen in Figure 3): the coefficient is large for nondurable while average hours are more variable for durable industries. Utilization contributes relatively less to service TFP: small coefficient combined with small variations of average hours. This implies more similar cyclical behavior of TFP and technology for service industries, as will be ascertained next.

Table 8a 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 1 for any industry group, although it is more distinctly greater than 1 for durable manufacturing and less than 1 for nondurable manufacturing and services; 2) the utilization coefficient β_i differs from its counterpart reported in Table 8 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 explain why the technology shock series derived using either set of coefficient estimates behave similarly in the decompositions and regressions to be analyzed next.

Given the observation that cyclical dynamics for multiple variables appear to have changed around the mid-1980s, we have also experimented with an alternative set of estimations 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 (15) plus the industry-specific intercept and the post-1973 term. As explained above, our baseline case sets $\mu = 1$ for all industries. To be further conservative, we set β to zero for 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 private nonfarm industries, along with the select industries and industry groups are plotted in Figure 3, along with growth of VA, primary input and employment.

To aggregate across industries, $\mathrm{d}z_{it}$ and the utilization term $\beta_i \mathrm{d}h$ are first rescaled to obtain the VA-based technology and utilization terms $\mathrm{d}z_{it}^V$ and $\mu_i\, \mathrm{d}u_{it}^V$, respectively. These latter two terms are then summed across industries using industry value-added weights to compute their aggregate counterparts $\mathrm{d}u^V$ and $\mathrm{d}z^V$. We can obtain the decomposition of TFP-input correlation according to equation (14), repeated below (with μ set to 1) for convenience, to explore how much of the lower procyclicality of TFP is due to the true technology term and how much due to the utilization term.

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

Table 9 presents component terms of the decomposition for aggregate private industries as well as for the four industry groups. Panel A reports the overall correlation $\rho(\mathrm{d}t, \mathrm{d}x^V)$ and the contribution from utilization $\mathrm{d}u$ and technology $\mathrm{d}z$, before versus after 1984 and the difference.[38] Panel B reports the two correlations on the right hand side (between $\mathrm{d}u$, $\mathrm{d}z$ and $\mathrm{d}x^V$). Panel C lists volatilities of the three terms before and after 1984 and the ratio between the two subperiods; a ratio less than 1 means volatility has fallen after 1984.

For the 27 nonfarm private industries as a whole, it is clear that the correlation between technology and input growth has been negative throughout the sample years and declined but slightly after 1984. Nevertheless, technology accounts for three quarters of the decline in TFP's correlation with inputs (0.45 out of 0.61) because its volatility relative to TFP's has risen substantially to yield a fairly negative third term in (14). This increase in the volatility ratio comes about because technology's volatility remains about the same throughout the sample years whereas TFP's volatility has fallen substantially, reflecting the lower covariance between technology and the utilization term.

At the industry or sector level, the TFP-input correlation has declined for all but construction. The nonmanufacturing sector, especially the service industries, have experienced the greatest reduction. These industries also show the largest decline in technology's correlation with inputs, nearly of the same

[38] The slight discrepancy between $\rho(\mathrm{d}t, \mathrm{d}x^V)$ and the sum of components stems from the fact that $\mathrm{d}z$ is computed using the time-series-average revenue shares of factors whereas standard TFP is calculated using time-varying weights.

magnitude as the decline in the TFP-input correlation. The similar behavior between TFP and technology for service industries is the result of relatively small utilization terms—small fluctuations of detrended hours combined with a comparatively small coefficient. The change in technology's cyclicality thus more than accounts for the diminished procyclicality of service industries' TFP. By comparison, technology contributes about 50 and 60 percent to the decline in TFP-input correlation for nondurable and durable manufacturing, respectively.

To further explore the lower covariance between technology and the utilization term 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-84 dummy variable (D_{post84}) equal to 1 after 1984 and 0 otherwise.[39] Given the established fact that output and inputs have become less volatile after 1984 (see for example Stock and Watson, 2002), we also allow the volatility of the residual to change.

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

$$\sigma\left(\varepsilon_{gt}\right) = \alpha_\varepsilon + \eta D_{post84} . \tag{17}$$

$\mathrm{d}g_t$ is the aggregate output or input variable of interest, 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 a la Jordà (2005) to the extent the technology series are correctly identified shocks. We apply maximum likelihood estimator in order to also estimate the change in residual volatility.[40]

Results of these regressions are presented in Table 10. Arguably the most notable feature is that detrended average hours and in turn utilization in fact respond more negatively to same-period technology shocks after 1984. The decline in the coefficient is both economically large and statistically significant (falls by 0.718 from the pre-1984 level of -1.215 for utilization, for example). Nevertheless, this decline is more than offset by the contribution from technology so that TFP, which is the sum of technology and utilization (given μ = 1), actually changes from a negative response before 1984 to

[39] These regressions do not account for the uncertainty concerning the timing of the change and thus are biased toward finding significant breaks, as discussed above in the section analyzing aggregate data.

[40] We have 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—the technology shocks are themselves estimated. These regressions however do not allow residual variance to change. Nevertheless, the coefficients on dz and its lags are qualitatively the same.

essentially a zero response to contemporaneous technology shocks after 1984.[41] This renders TFP less correlated with inputs, which now respond more negatively, albeit less significantly than average hours or insignificantly, to technology shocks. In the subsequent four periods, especially the next two periods, detrended average hours and hence utilization rebound more positively after 1984. By comparison, employment also appears more responsive, although insignificantly, after 1984.

We then ascertain that the pattern of more negative response of average hours to technology shocks in the same period is also present at the individual industry level. Table 11 reports the summary statistics of the coefficient estimates from 27 industry-level regressions as specified in (17) with utilization being the dependent variable. The response of utilization to technology shocks in the same period has become more negative on average across industries. Note that the mean coefficient is a simple average across industries, whereas the corresponding coefficient from Table 10 is akin to a VA weighted average. By comparison, the responses in subsequent periods are not as different before versus after 1984. In sum, the more negative contemporaneous response of utilization to technology shocks seems broad-based.

As a robustness check, we estimate the same set of regressions using technology shocks derived using the production-function coefficients reported in Table 8a, which do not constrain the returns to scale parameter. The regression output is displayed in Table B.3. The main results are qualitatively the same as those in Table 10. That is, average hours and hence utilization have become more responsive to technology shocks, both contracting more contemporaneously and rebounding more later. Output and total hours respond in the same direction as in Table 10 but are no longer significant in the same period.

Hence, the overall pattern is that detrended average hours and thus utilization have become more responsive to technology shocks since the mid-1980s. The more negative reaction in the same period is a further departure from the standard RBC model. Moreover, it is 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 and monitored intensive margin is average hours, so we would expect firms to utilize the hours per worker margin less relative to the employment margin if it is the latter's adjustment cost that has fallen.

One potential reason that the sensitivity of hours per worker to technology shocks has not diminished relative to that of employment is if the persistence of technology shocks has fallen. By the same logic as demonstrated in Ramey and Vine (2006), firms would utilize the intensive margin relatively

[41] Note that if dz were the single regressor, then the coefficient of regressing dt on dz can 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.

more to adjust inputs if shocks become less persistent, which makes paying the adjustment cost for the extensive margin less worthwhile. However, as reported in Table 12, regression estimates, which imposes a MA(1) process on the error term and includes a post-1973 dummy variable for a lower growth rate, of the first autoregressive coefficient interacted with the post-1984 dummy variable in fact yields more evidence for an *increase* instead of a decrease in the persistence of technology shocks after 1984. That is, we estimate the following regression and find a significantly positive β_1:[42]

$$\mathrm{d}z_t = \alpha + \alpha_1 D_{post73} + \beta \mathrm{d}z_{t-1} + \beta_1 \mathrm{d}z_{t-1} D_{post84} + e_t - e_{t-1}\,. \qquad (18)$$

The greater sensitivity of average hours can be reconciled with the no less persistent technology shocks if we interpret greater flexibility of labor arrangements more broadly. That is, various reforms may have enabled firms to adjust both the extensive and the intensive margins more cheaply in response to shocks. On the other hand, private sector's reaction to technology shocks is also influenced by the degree to which the monetary authority accommodates the shocks. In this regard, the increase in the absolute magnitude of average hours' response to technology shocks is potentially inconsistent with greater monetary policy accommodation of technology shocks as advocated by Gali, Lopez-Salido and Valles (2003). Nor is the finding, reported in the last column of Table 10, that prices in fact fall significantly more in the two years following a positive technology shock in the post-1984 sample.[43]

The only way to reconcile the findings is to recognize that Gali et al. (2003) identify technology shocks as those that raise the level of productivity permanently whereas the technology shocks here contain not only permanent components but also transitory ones. Since the mid 1980s, the central bank has somehow become better at accommodating permanent shocks but not transitory ones. This seems a plausible conjecture in that inflation depends more on the highly persistent components of technology shocks, and the central bank thus is presumably better able to extract signals of this type of shocks. This interpretation implies that a larger fraction of the technology shocks requiring private reaction are of the transitory type, consistent with our finding that the intensive margin of labor input has become more (negatively) responsive to technology shocks.

Our finding that there is little change in the correlation between true technology and inputs, once variations in unmeasured input are accounted for, suggests that changes in the magnitude and cyclical behavior of intangible investment is not necessary to explain the lower procyclicality of LP and TFP.

[42] This regression specification is derived from assuming 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 have also tried estimating a similarly specified regression of log levels of z, and the counterpart to β_1 is again positive.

[43] Note that the impact VA deflator is the only variable that shows a significantly lower level after 1984, reflecting the steady deflation since the mid-1980s through the 1990s and even early 2000s.

Moreover, there does not appear to be any intuitive connection between the greater sensitivity of average hours to technology shocks and the intangible investment story. One can imagine the following elaborate interpretation: the positive technology shocks result from less unmeasured investment relative to market output, which coincides with less output overall, and firms thus cut total inputs. Firms would especially cut average hours if they anticipate the adjustment to be short-lived. There is, however, no corroborating evidence to support this conjecture.

4.6 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 more efficient allocation of factors. Basu and Fernald (2002) derive the decomposition of aggregate TFP into aggregate technology versus allocation terms related to cross-section dispersion in markup and (shadow) marginal revenue products of all inputs due to frictions in input or output markets that preclude perfect mobility of resources across firms or industries. In the context of this study, the natural question is to what extent the change in TFP's cyclicality is attributed to contribution from technology versus resource allocation.

In this section, we conduct such a decomposition of aggregate TFP of private nonfarm industries and compare the contribution of different components before versus after 1984. This can help shed light on the likely causes for the change in the cyclicality of aggregate productivity. For instance, more flexible input and output markets can be expected to effect more efficient allocation of labor and capital to industries offering higher marginal product so that the allocation terms contribute to the less procyclical TFP, whereas increased intangible investment is by comparison much less likely to have played a role.

The relationship between aggregate TFP (dt) and aggregate technology (dz^V) can be expressed as follows (see Appendix I for details of the derivation):

$$\mathrm{d}t_t = \left[\left(\bar{\mu}-1\right)\mathrm{d}x_t^V + \mathrm{d}\bar{u}_t^V + R_{M,t}\right] + R_{\mu,t} + \bar{\mu}\left(R_{L,t} + R_{K,t}\right) + \mathrm{d}z_t^V . \tag{19}$$

dt is aggregate TFP growth, defined as dv - dx^V, where dv is the growth of aggregate value added, and dx^V the growth of measured primary inputs (that is, capital and labor). $\bar{\mu}$ is the VA-weighted-average of markups on gross output. $\mathrm{d}\bar{u}_t^V$ denotes the first-order contribution from unmeasured inputs.[44] R_μ denotes the contribution from distributions of production across firms with different markups, while R_M,

[44] 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).

R_K, and R_L denote contribution from allocations of intermediate, capital and labor inputs to firms with different *shadow* prices for the respective input. The last term $\mathrm{d}z^V$ is the VA-weighted-average growth rate of firm or industry VA-augmenting technology. (See Appendix I for the exact expressions of these terms.)

The first term in equation (19) 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. Note that $\mathrm{d}x^V$ denotes only those measured inputs, while $\mathrm{d}\overline{u}_t^V$ captures the unmeasured inputs. We follow BFK (2006) in using the growth of average hours per worker to proxy for the unmeasured variation in primary inputs. The contribution to aggregate productivity from reallocations of capital and labor is also scaled up by the Domar weights (i.e., 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, and measured as well as unmeasured primary input growth, that is:

$$R \equiv R_\mu + R_M + \overline{\mu}\left(R_L + R_K\right) = \mathrm{d}t - \left(\overline{\mu} - 1\right)dx^V - \mathrm{d}\overline{u}^V - \mathrm{d}z^V. \tag{20}$$

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 (19) can be carried out using estimates of μ, $\mu\mathrm{d}u$ and $\mathrm{d}z^V$ derived above. Table 13 presents the result based on the CRS production function coefficients reported in Table 8. It is obvious from equation (19) that with μ constrained to 1, all but two—R_L and R_K—of the allocative-efficiency terms disappear. Hence it is not surprising that the allocation terms contribute only about ten percent to the change in TFP's correlation with inputs. Instead, the bulk is accounted for 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, more than offset by the outsized decline in utilization's correlation with VA.

It is probably also not surprising that once we relax the CRS constraint, the allocation terms become more important contributors to the lower correlation between TFP and inputs as well as output,

as can be seen in Table 14. Given the uncertainty surrounding the production function coefficient estimate, we would interpret these results 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, between these two sets of estimates, utilization and allocation together account for between 25 to 50 percent of the decline in TFP's correlation with inputs.

The sizable contribution from within-industry forces, including technology and possibly input scale related to non-CRS, to the change in TFP's cyclicality can be consistent with the proposed story of more flexible adjustments of inputs to the extent that we think the effect should manifest first and more pronounced at individual industry level, as opposed to across industries.

4.7 Cross-Industry Evidence for Greater Labor Market Flexibility

Last we explore to what extent the mechanism proposed by Gali and van Rens (2010) is borne out by the cross-industry relationship between the change in TFP's cyclicality and changes in other attributes. In particular, we examine the cross-section relationship between the change in TFP's comovement with input and the change in the ratio of input to output volatility. Gali and van Rens's (2010) model implies a strong negative relationship between the two variables: 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 changes in union membership is a decent 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 TFP's procyclicality.

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 becomes relative to its VA, the less correlated its TFP with inputs. The slope coefficient is fairly significant if we regress the latter on the former.[45] Figure 5 plots the analogous relationship with employment substituting for total hours. It is remarkable, although not surprising, how similar the two relationships are, since most of the variation in total hours is accounted for by changes in employment. Another notable feature is the 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 by comparison. Note that all of these are unconditional relationships, reflecting the joint outcome of institutional changes

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

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 between employment and average hours per worker, as evidenced by Figure 6. Combined with the result from the previous section, this suggests that reforms to labor market institutions are more broad-based than just lowering the cost of adjusting the extensive margin—hiring and firing. The reforms have likely also made it less costly to alter the intensive margin, such as by making the marginal cost of raising average hours less steep.

For more direct evidence of the impact of changes in labor market institutions on productivity's cyclical property, we examine the cross-industry pattern of the change in union membership rate between 1983 and 2007 and the change in the industry's TFP-input correlation. The union membership data by industry are compiled by Barry Hirsch and David Macpherson; see Hirsch (2008) for details about the data.[46] As shown in Figure 7, the share of union members in total employees has fallen in virtually every industry. However, there is hardly any discernable connection between the cumulative change in union membership rate since 1983 and the change in TFP-input correlation at the industry level.[47] This lack of any relationship seems puzzling, even though one can think of reasons why union membership rates may not affect the flexibility of adjusting labor input. For example, it is possible that unions in fact internalize more of the cost of inefficient adjustments in industries where they represent a higher fraction of workers. So a shrinking membership can actually raise the adjustment cost, depending on how influencial unions used to be.

In short, there is evidence along some dimensions supporting the proposed explanation that more flexible labor arrangements are largely responsible for the decline in the procyclical behavior of productivity. On the other hand, 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 consistent with the evidence along all the dimensions.

[46] 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 2002 NAICS system and then the KLEMS industry codes.
[47] The pattern is rather similar if, instead of membership rate, we use union coverage rate.

V. Conclusion

Apart from being of interest to researchers wanting to understand potential changes of the structural dynamic governing an economy, it is important also for monetary policy makers to gauge the cyclicality of productivity. For one thing, it affords them more accurate decomposition of the actual growth rate into trend versus cycle components. This study attemps to gain a better understanding of the forces underlying the diminished procyclicality of aggregate productivity by using industry data to analyze changes in the cyclical property of productivity across industries.

It finds 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 across industries. Applying a method developed in previous studies, we correct total factor productivity for unmeasured input utilization to evaluate relative contribution of technology and utilization to the change in productivity's cyclical dynamics. We then discover that the cyclicality of technology has changed little. The main reason for TFP's lower correlations with output and inputs is that the technology term, which has remained countercyclical throughout the sample period, accounts for a larger share of TFP's correlations with inputs after the mid-1980s.

In fact, we find evidence both in the aggregate and at the industry level that inputs, especially average hours per worker and in turn utilization *contracts* more in response to a positive technology shock in the period since the mid-1980s even though the shocks are no less persistent. This finding warrants more analysis since it is potentially inconsistent with the notion that monetary policy has improved in its accommodation of technology shocks. Utilization's effect, however, is more than offset by the greater contribution from the technology term so that overall TFP responds more positively, and thus becomes less correlated with inputs and output over this period.

The fact that employment has not become more responsive than average hours per worker to technology shocks since the mid-1980s is inconsistent with the explanation purely based on lower hiring and firing cost. On the other hand, there is a robust relationship across industries between the decline in TFP's correlation with inputs and output and the relative increase in the volatility of employment and total hours vis-à-vis value added. These findings together suggest that whatever reforms that have enhanced the flexibility in labor markets have likely enabled firms to reduce the cost of adjusting both extensive and intensive margins of labor. At the same time, the more flexible labor market seems to have mostly led to more efficient input adjustments within individual industries, 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 a quarter of the reduction in the procyclicality of TFP.

To the extent that we believe these findings constitute reasonable evidence for greater flexibility in the labor market, it has the implication that policy makers should down-weight the performance of productivity during downturns in their estimate of the underlying trend growth. It also leads to the question how is the greater flexibility consistent with jobless recoveries. Berger (2012) provides a plausible explanation, but this issue warrants further analysis.

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Figure 1. Bandpass-filtered labor productivity, total factor productivity and output

Notes: This figure plots the bandpass filtered time series of (the logarithms of) labor productivity and output of the private business sector, along with total factor productivity for comparison. The vertical line marks 1984:Q1.

Figure 2a. Change in correlation between LP and primary input growth: FD- versus HP-filtered

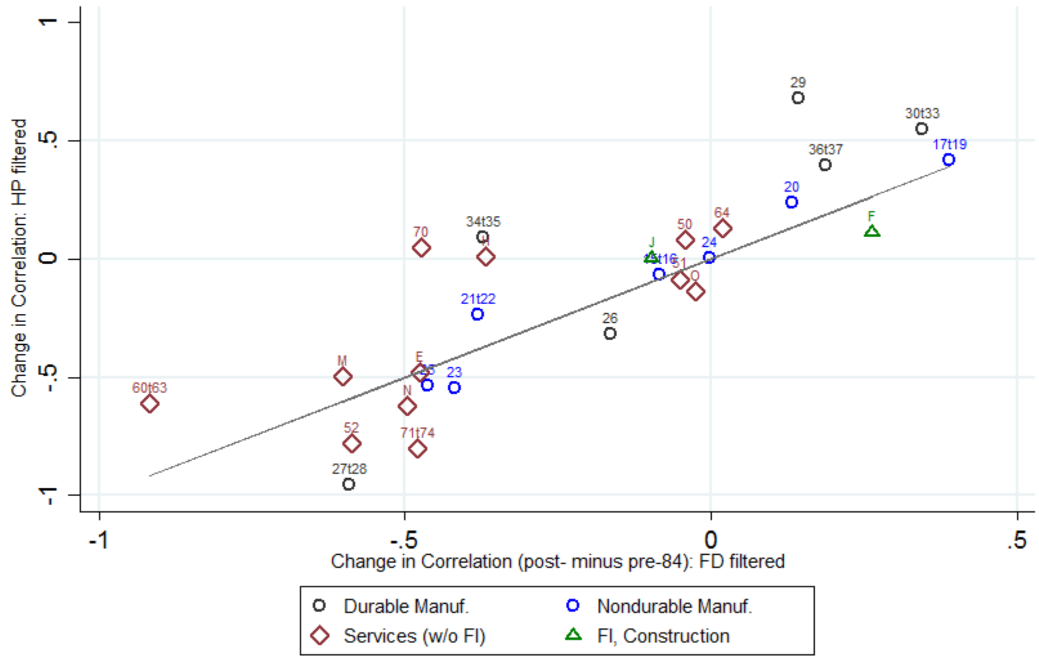
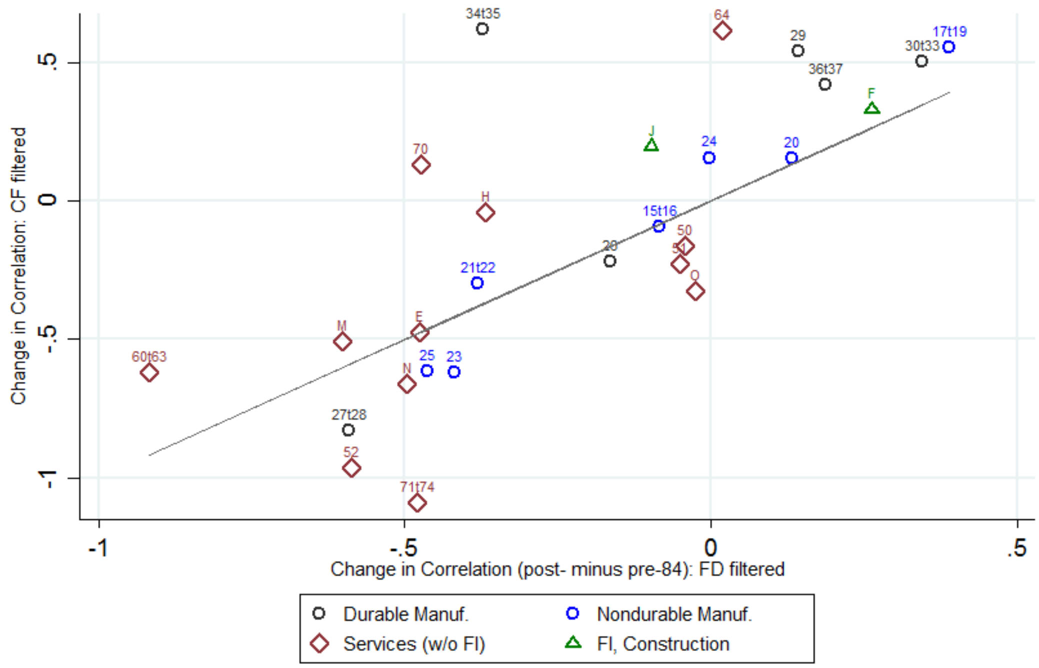
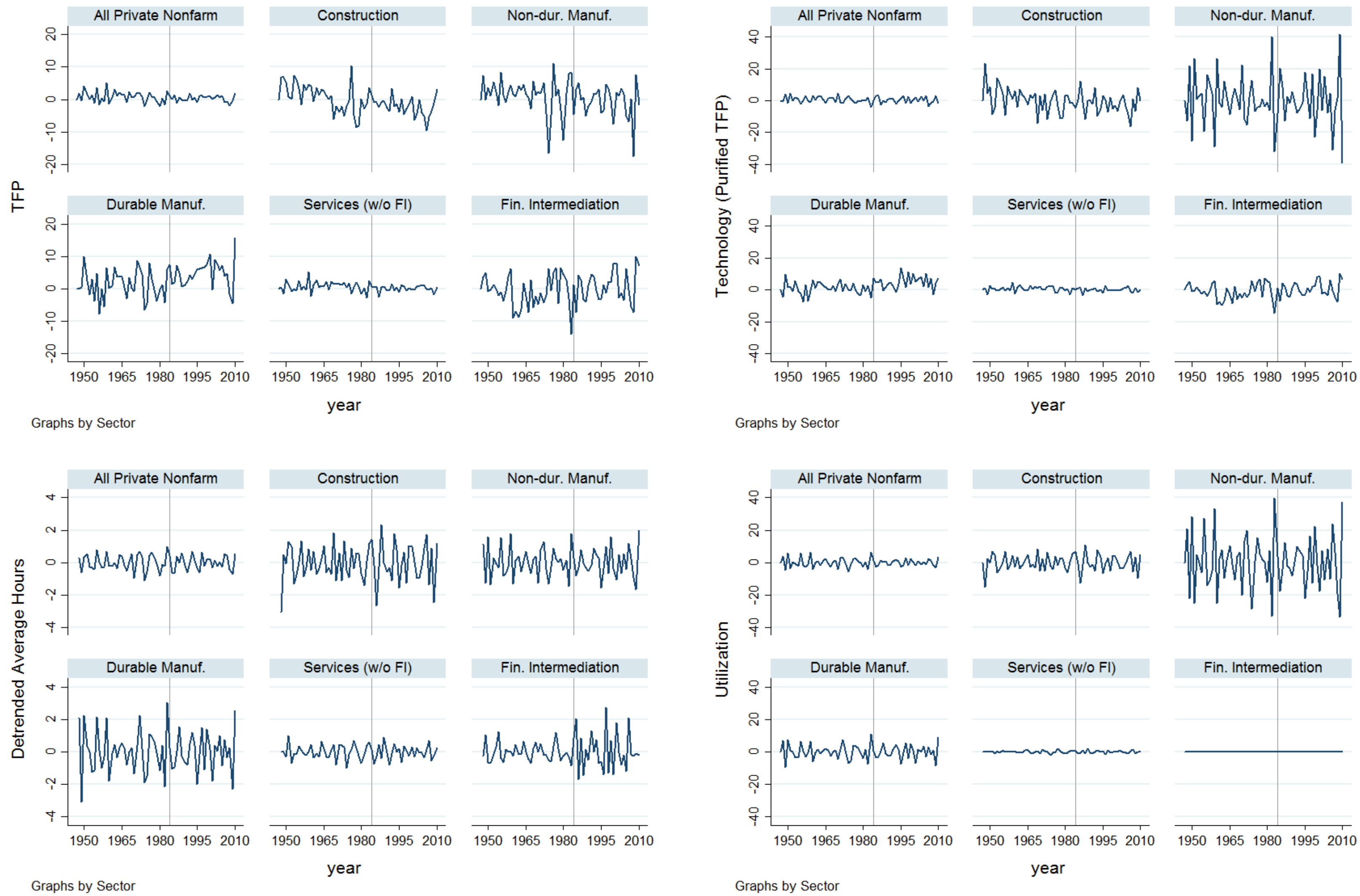


Figure 2b. Change in correlation between LP and primary input growth: FD- versus CF-filtered



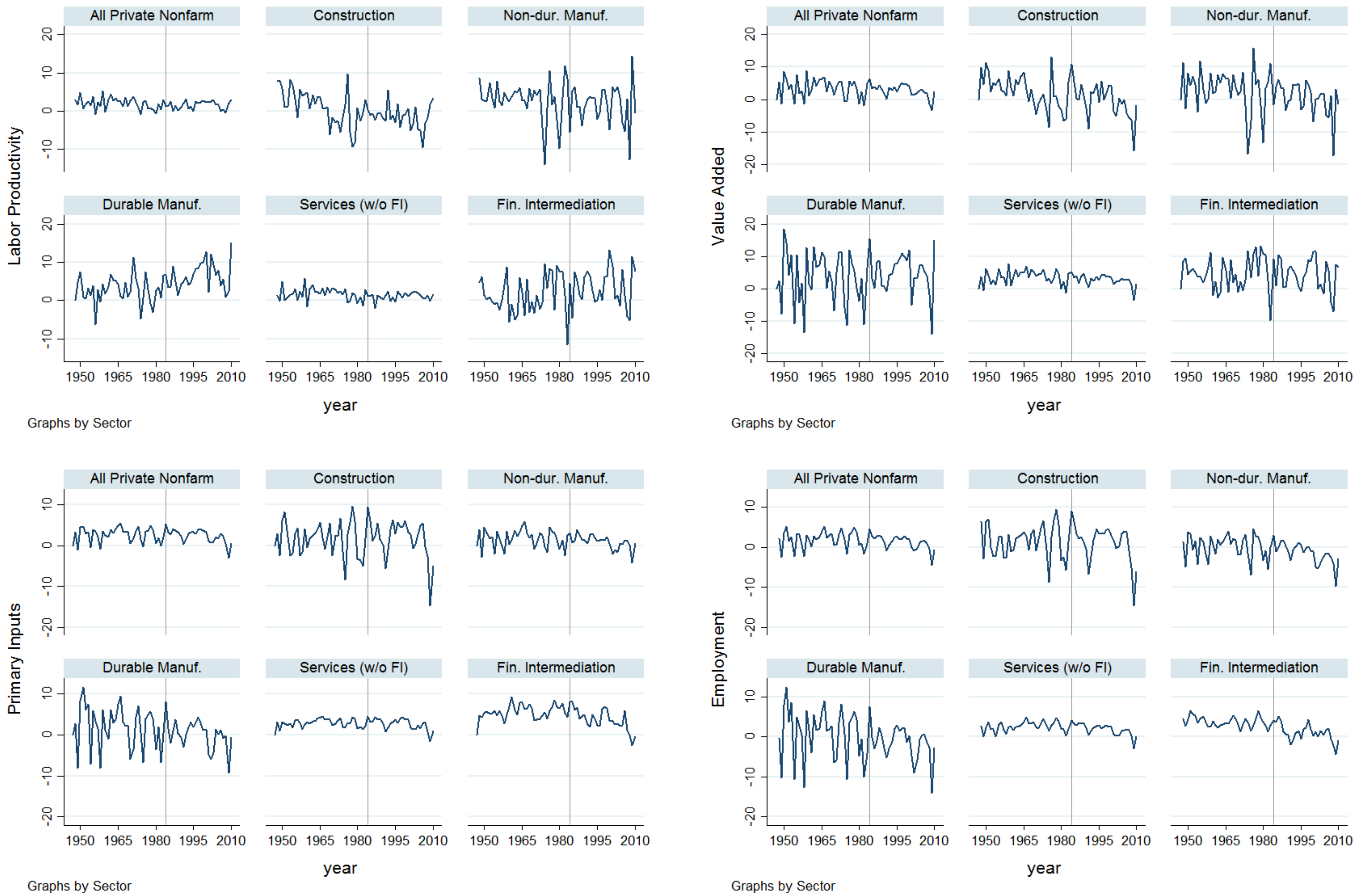
Notes: These charts depict changes in the correlation between LP and input growth by industry based on different filters. HP: Hodrick-Prescott filter with the standard parameter for annual data; CF: Christiano-Fitzgerald filter, a form of bandpass filter with band 2 to 8 years; FD: first-difference,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

Figure 3. Productivity, technology, value added and primary inputs of all private nonfarm industries and select industry groups



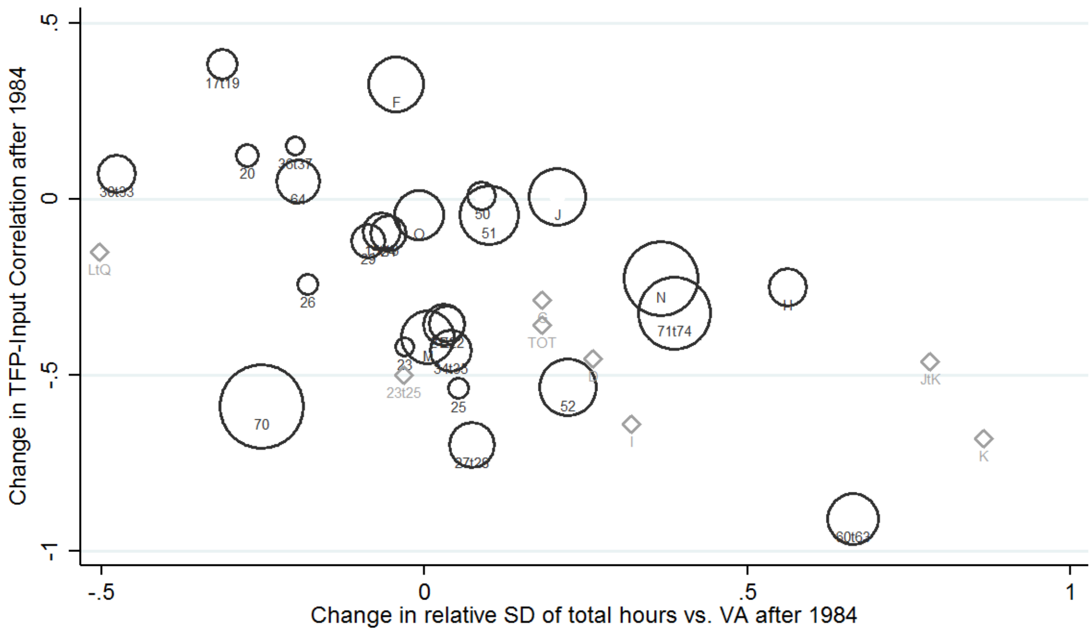
Notes: All the variables are growth rates in percent. The grey vertical line marks year 1984. Utilization is restricted to zero for Financial Intermediation.

Figure 3. (continued) Labor productivity, value added and primary inputs of all private nonfarm industries and select industry groups



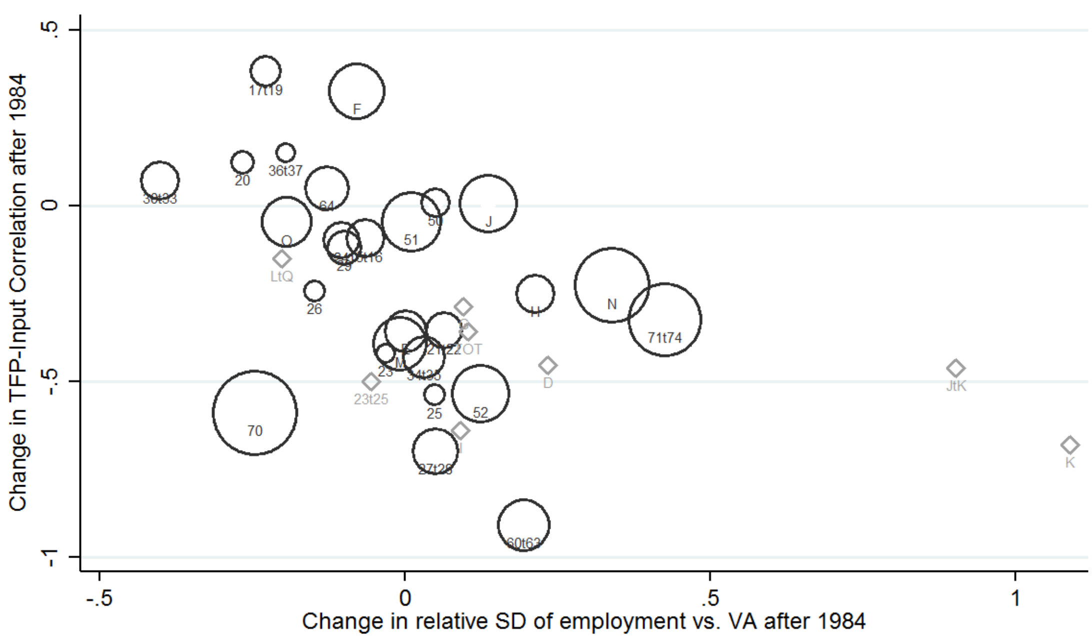
Notes: All the variables are growth rates in percent. The grey vertical line marks year 1984. Utilization is restricted to zero for Financial Intermediation.

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])



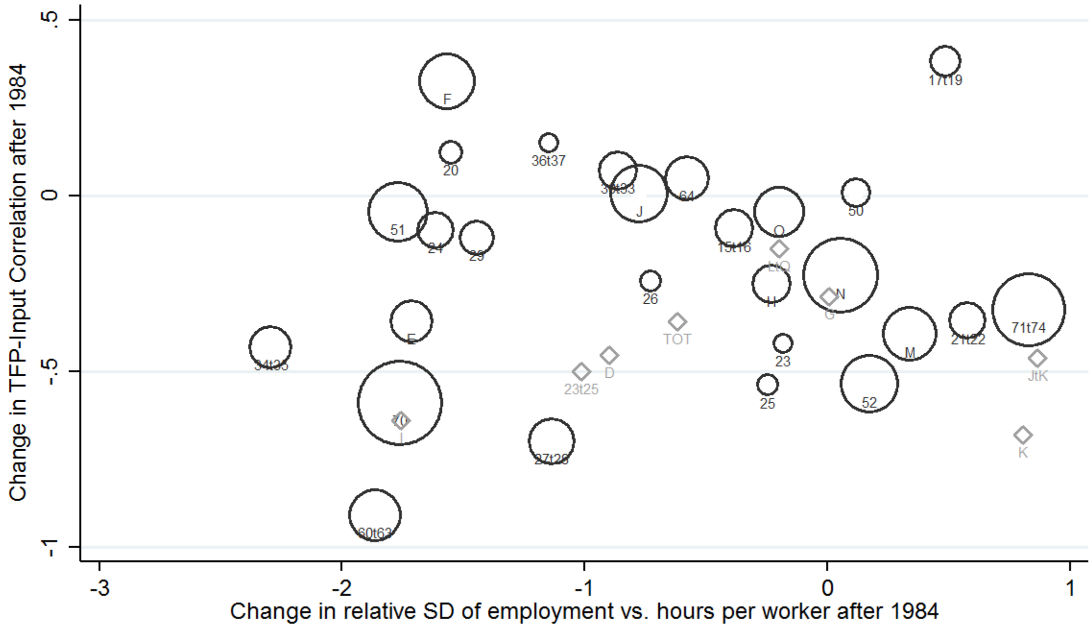
Notes: The black circles depict individual industries while the light grey diamonds depict sectors and the total economy in the Jorgenson et al. dataset. Size of the circle proportional to an industry's time-series average VA share.

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])



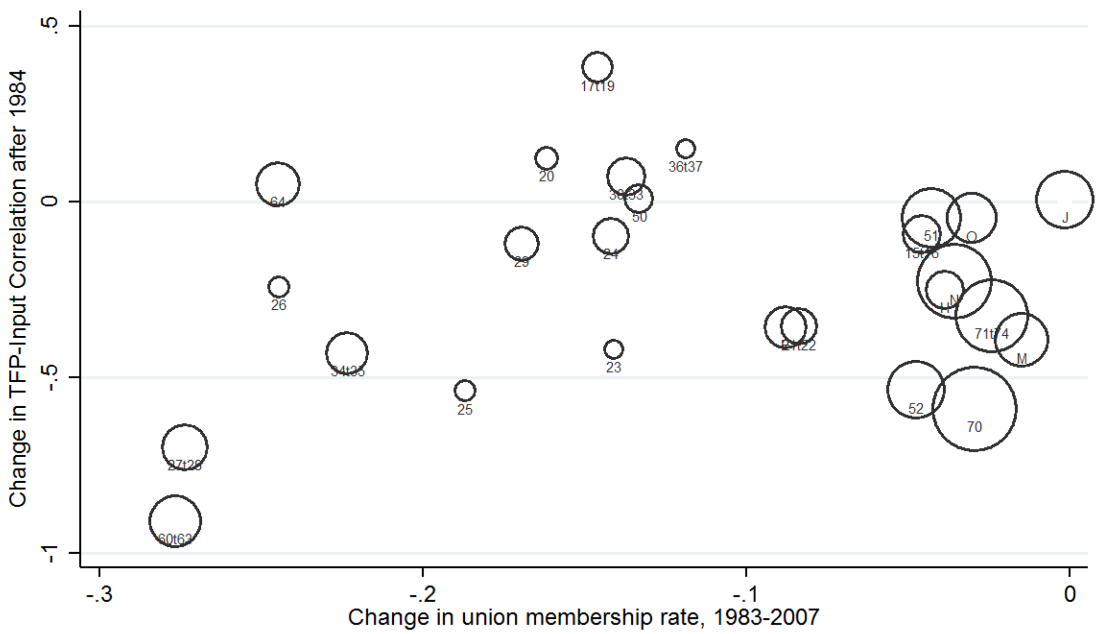
Notes: Same as for Figure 4.

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: Same as for Figure 4.

Figure 7. Cross-industry pattern of change in TFP-VA correlation after 1984 versus change in union membership since 1983



Notes: The black circles depict individual industries with the size of the circle proportional to an industry's time-series average VA share.

Table 1. Cyclical correlation between labor productivity and output: 1950 - 2009

Panel A. Quarterly data 1950:Q1 - 2009:Q2

Filter	1950Q1 - 2009Q4	1950Q1 - 1983Q4	1984Q1 - 2009Q4	Subperiod Diff.
Bandpass	0.441	0.572	0.086	-0.486
HP	0.427	0.588	0.006	-0.582
CF	0.480	0.594	0.146	-0.448
First Difference	0.673	0.725	0.490	-0.235

Note: Bandpass filter with frequency band 6 - 32 quarters. HP: Hodrick-Prescott filter with λ = 1600. CF: Christiano-Fitzgerald (2003) filter, with frequency band 6 - 32 quarters.

Panel B. Annual data 1950 - 2009

Filter	1950 - 2009	1950 - 1983	1984 - 2009	Subperiod Diff.
Bandpass	0.392	0.553	-0.067	-0.620
HP	0.357	0.562	-0.139	-0.701
CF	0.457	0.585	0.098	-0.487
First Difference	0.497	0.649	0.090	-0.559

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

Table 1a. Cyclical correlation between labor productivity and output: 1960 - 2007

Panel A. Quarterly data 1960:Q1 - 2007:Q4

Filter	1960Q1 - 2007Q4	1960Q1 - 1983Q4	1984Q1 - 2007Q4	Subperiod Diff.
Bandpass	0.444	0.614	0.010	-0.604
HP	0.455	0.635	-0.039	-0.674
CF	0.528	0.641	0.211	-0.430
First Difference	0.703	0.751	0.565	-0.186

Note: See Panel A of Table 1 above.

Panel B. Annual data 1960 - 2007

Filter	1960 - 2007	1960 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.413	0.596	-0.029	-0.625
HP	0.381	0.603	-0.170	-0.773
CF	0.513	0.627	0.216	-0.411
First Difference	0.487	0.642	0.137	-0.505

Note: See Panel B of Table 1 above.

Table 2. Formal trend break tests

Panel A. Bai-Perron break tests: sample period 1950:Q1 - 2009:Q2

Break in the slope coefficient	
a) supF tests against a fixed number of breaks:	
0 versus 1 break: 4.4247	Critical value at 10%: 7.04
Break date: 1986:Q3	
b) Dmax tests against an unknown number of breaks:	
Test statistic: 4.4247	Critical value at 10%: 7.46
Break in both the intercept and slope coefficient	
a) supF tests against a fixed number of breaks:	
0 versus 1 break: 13.9747	Critical value at 1%: 12.15
Break date: 1987:Q1	
b) Dmax tests against an unknown number of breaks:	
Test statistic: 22.0747	Critical value at 1%: 15.41

Panel B. Bai-Perron break tests: sample period 1960:Q1 - 2007:Q4

Break in the slope coefficient	
a) supF tests against a fixed number of breaks:	
0 versus 1 break: 7.0665	Critical value at 10%: 7.04
Break date: 1986:Q3	
b) Dmax tests against an unknown number of breaks:	
Test statistic: 7.0665	Critical value at 10%: 7.46
Break in both the intercept and slope coefficient	
a) supF tests against a fixed number of breaks:	
0 versus 1 break: 8.7153	Critical value at 10%: 9.81
Break date: 1986:Q3	
b) Dmax tests against an unknown number of breaks:	
Test statistic: 23.9915	Critical value at 1%: 15.41

Note: Top two panels of this table reports the Bai-Perron (2003) test statistics using aggregate U.S. output and labor productivity data as computed in Fernald (2012a).

Panel C. Elliott-Müller qLL test statistic for time varying coefficients 1950:Q1 - 2007:Q4

Break in the slope coefficient	
0 versus 1 break: -7.132	Critical value at 10%: -7.14
	Critical value at 5%: -8.36

Note: This panel reports the Elliot- Müller (2006) test statistics using aggregate U.S. output and labor productivity data as computed in Fernald (2012a). The Stata routine qll is written by Kit Baum. The long-run variance computed using 24 lags.

Table 3. Cyclical correlation between TFP and output: 1950 - 2009

Panel A. Quarterly data 1950:Q1 - 2009:Q2

Filter	1950Q1 - 2009Q4	1950Q1 - 1983Q4	1984Q1 - 2009Q4	Subperiod Diff.
Bandpass	0.820	0.872	0.637	-0.235
HP	0.820	0.876	0.630	-0.246
CF	0.840	0.876	0.725	-0.151
First Difference	0.865	0.898	0.738	-0.160

Note: Bandpass filter with frequency band 6 - 32 quarters. HP: Hodrick-Prescott filter with $\lambda = 1600$. CF: Christiano-Fitzgerald (2003) filter, with frequency band 6 - 32 quarters.

Panel B. Annual data 1950 - 2009

Filter	1950 - 2009	1950 - 1983	1984 - 2009	Subperiod Diff.
Bandpass	0.800	0.869	0.490	-0.379
HP	0.808	0.875	0.586	-0.289
CF	0.836	0.876	0.712	-0.164
First Difference	0.818	0.875	0.671	-0.204

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 3a. Cyclical correlation between TFP and output: 1960 - 2007

Panel A. Quarterly data 1960:Q1 - 2007:Q4

Filter	1960Q1 - 2007Q4	1960Q1 - 1983Q4	1984Q1 - 2007Q4	Subperiod Diff.
Bandpass	0.812	0.879	0.560	-0.319
HP	0.817	0.886	0.538	-0.348
CF	0.84	0.884	0.695	-0.189
First Difference	0.866	0.904	0.740	-0.164

Note: See Panel A of Table 3 above.

Panel B. Annual data 1960 - 2007

Filter	1960 - 2007	1960 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.805	0.876	0.544	-0.332
HP	0.803	0.883	0.485	-0.398
CF	0.837	0.882	0.696	-0.186
First Difference	0.797	0.874	0.553	-0.321

Note: See Panel B of Table 3 above.

Table 4. Cyclical correlation between utilization-adjusted TFP and output: 1950 - 2009

Panel A. Quarterly data 1950:Q1 - 2009:Q2

Filter	1950Q1 - 2009Q4	1950Q1 - 1983Q4	1984Q1 - 2009Q4	Subperiod Diff.
Bandpass	-0.168	-0.154	-0.217	-0.063
HP	-0.061	0.013	-0.252	-0.265
CF	-0.277	-0.263	-0.326	-0.063
First Difference	0.446	0.456	0.409	-0.047

Note: Bandpass filter with frequency band 6 - 32 quarters. HP: Hodrick-Prescott filter with λ = 1600. CF: Christiano-Fitzgerald (2003) filter, with frequency band 6 - 32 quarters.

Panel B. Annual data 1950 - 2009

Filter	1950 - 2009	1950 - 1983	1984 - 2009	Subperiod Diff.
Bandpass	-0.087	-0.064	-0.160	-0.096
HP	-0.119	-0.009	-0.375	-0.366
CF	-0.235	-0.183	-0.358	-0.175
First Difference	0.014	0.018	-0.029	-0.047

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

Table 4a. Cyclical correlation between utilization-adjusted TFP and output: 1960 - 2007

Panel A. Quarterly data 1960:Q1 - 2007:Q4

Filter	1960 - 2007	1960 - 1983	1984 - 2007	Subperiod Diff.
Bandpass	0.071	0.175	-0.103	-0.278
HP	0.188	0.324	-0.070	-0.394
CF	0.013	0.086	-0.096	-0.182
First Difference	0.602	0.611	0.594	-0.017

Note: See Panel A of Table 4 above.

Panel B. Annual data 1960 - 2007

Filter	1960Q1 - 2007Q4	1960Q1 - 1983Q4	1984Q1 - 2007Q4	Subperiod Diff.
Bandpass	0.104	0.267	-0.139	-0.406
HP	0.128	0.322	-0.188	-0.510
CF	0.056	0.186	-0.113	-0.299
First Difference	0.213	0.223	0.212	-0.011

Note: See Panel B of Table 4 above.

Table 5. 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 in 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 in 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 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 $\rho(\mathrm{d}a,\ \mathrm{d}x^V)$, which serves as a summary measure of how similar the cross-industry pattern is using different filters. For the corresponding cross-industry scatterplots, see Figures 2a and 2b.

Table 6. 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 7. 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 aggregate TFP-input correlation and its change after 1984 into weighted average within- versus cross-industry components. The contributions are normalized to a equal-weighted per industry pair basis and scaled to basis points to facilitate comparison.

Table 8. Gross output production function parameter estimates: with CRS constraint

		Manufacturing		
RHS	Construction	Nondurable	Durable	Non-manufacturing
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 consisted 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 8a. Gross output production function parameter estimates: without CRS constraint

		Manufacturing		
RHS	Construction	Nondurable	Durable	Non-manufacturing
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 consisted 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 9. Decomposition of TFP-input correlation $\rho(\mathrm{d}t, \mathrm{d}x^V)$, and its change after 1984

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

	$\rho(\mathrm{d}t, \mathrm{d}x^V)$			Contribution of $\mathrm{d}u$ to $\rho(\mathrm{d}t, \mathrm{d}x^V)$			Contribution of $\mathrm{d}z$ 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 private nonfarm 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 ($\mathrm{d}u$) and technology ($\mathrm{d}z$) with input growth ($\mathrm{d}x^V$)

	$\rho(\mathrm{d}u, \mathrm{d}x^V)$			$\rho(\mathrm{d}z, \mathrm{d}x^V)$		
	Before 1984	**After 1984**	**Change**	**Before 1984**	**After 1984**	**Change**
Aggregate private nonfarm 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 ($\mathrm{d}t$), utilization ($\mathrm{d}u$) and technology ($\mathrm{d}z$)

	$\sigma(\mathrm{d}t)$			$\sigma(\mathrm{d}u)$			$\sigma(\mathrm{d}z)$		
	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 private nonfarm 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 afterward (based on the CRS production function parameters, reported in Table 8)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RHS	**VA**	**Inputs**	**Total hours**	**Employment**	**Detrended hours**	**Utilization**	**TFP (VA-basis)**	**LP**	**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}	0.0901	-0.170	-0.258	-0.0778	**-0.178*** **	**-0.718*** **	**0.260*** **	0.348***	-0.163
	[0.165]	[0.141]	[0.178]	[0.155]	**[0.0231]**	**[0.0761]**	**[0.0805]**	[0.101]	[0.102]
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}	0.0347	-0.132	-0.196	-0.179	**-0.0171**	**0.149***	**0.166***	0.231**	-0.222**
	[0.175]	[0.149]	[0.188]	[0.164]	**[0.0245]**	**[0.0804]**	**[0.0851]**	[0.107]	[0.108]
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}	0.270	0.0596	0.0683	0.0153	**0.0493***	**0.234*** **	**0.210** **	0.202*	-0.250**
	[0.189]	[0.162]	[0.204]	[0.177]	**[0.0265]**	**[0.0872]**	**[0.0922]**	[0.116]	[0.117]
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}	0.173	0.0991	0.126	0.0987	**0.0334**	**0.0920**	**0.0739**	0.0471	-0.0865
	[0.194]	[0.165]	[0.208]	[0.181]	**[0.0271]**	**[0.0892]**	**[0.0944]**	[0.119]	[0.120]
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}	0.163	0.0366	0.0867	0.0581	**0.0378**	**0.139***	**0.126**	0.0767	-0.0508
	[0.173]	[0.148]	[0.186]	[0.162]	**[0.0243]**	**[0.0798]**	**[0.0845]**	[0.106]	[0.107]
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
Chi-squared	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 contribution from technology versus from input utilization and allocation. The top panel decomposed 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 contribution from technology versus from input utilization and allocation. The top panel decomposed 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 formulae 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 (dy) equals revenue-share-weighted composite input growth scaled by the markup, plus gross-output augmenting technology change, dz. Inputs here include both measured components (dx, such as labor and capital) and unmeasured elements (du, such as utilization rate). For any industry i, this relationship can be written as:[48]

$$\mathrm{d}y_{it} = \mu_i\left(\mathrm{d}x_{it} + \mathrm{d}u_{it}\right) + \mathrm{d}z_{it} = \mu_i(s_{Li}\mathrm{d}l_{it} + s_{Ki}\mathrm{d}k_{it} + s_{Mi}\mathrm{d}m_{it} + \mathrm{d}u_{it}) + \mathrm{d}z_{it}\,. \tag{1}$$

dl, dk, and dm 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). du denotes the composite utilization term, including both labor effort and capital utilization.[49] 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 do not necessarily sum to 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.[50]

Treating dy as a Divisia index of dv and dm as Basu and Fernald (2002), we can show that equation (1) then implies (for clarity of exposition, subscript it for growth rates are omitted):

$$\mathrm{d}v := \frac{\mathrm{d}y - s_{Mi}\mathrm{d}m}{1-s_{Mi}} = \frac{\mu_i\left(\mathrm{d}x + \mathrm{d}u\right) + \mathrm{d}z - s_{Mi}\mathrm{d}m}{1-s_{Mi}} = \mu_i\left(dx^V + du^V\right) + \left(\mu_i - 1\right)\frac{s_{Mi}}{1-s_{Mi}}\mathrm{d}m + \mathrm{d}z^V\,, \tag{2}$$

[48] 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 and so there is no aggregation-related issues at the industry level.
[49] 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, wage premium paid to labor because of a longer work week.
[50] There may still be interesting cyclical variations in s_π, but we subsume them into variations in μ.

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:

$$\mathrm{d}x^V = \frac{s_{Li}}{1-s_{Mi}}\mathrm{d}l + \frac{s_{Ki}}{1-s_{Mi}}\mathrm{d}k \equiv s_{Li}^V \mathrm{d}l + s_{Ki}^V \mathrm{d}k\,, \tag{3}$$

$$\mathrm{d}u^V = \mathrm{d}u \big/ \left(1-s_{Mi}\right), \tag{4}$$

$$\mathrm{d}z^V = \mathrm{d}z \big/ \left(1-s_{Mi}\right). \tag{5}$$

$\mathrm{d}x^V$ is the growth rate of primary inputs, $\mathrm{d}u^V$ 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 nominal VA share of labor and capital, respectively. Obviously, with perfect competition, equation (2) 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 is 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 $\mu^V = \mu\left(1-s_M\right)\big/\left(1-\mu s_M\right)$, 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 (2) then implies that the VA-base TFP, $\mathrm{d}t$, defined as $\mathrm{d}v$ - $\mathrm{d}x^V$, equals:

$$\mathrm{d}t_{it} = \left(\mu_i - 1\right) dx_{it}^V + \mu_i du_{it}^V + \left(\mu_i - 1\right)\frac{s_{Mi}}{1-s_{Mi}}\mathrm{d}m_{it} + \mathrm{d}z_{it}^V\,. \tag{6}$$

Obviously, with perfect competition, $\mathrm{d}t = \mathrm{d}u^V + \mathrm{d}z^V$, that is, TFP still measures both true technology and utilization (on a VA scale), but there will no longer be contribution from inputs due to markup. This can be more clearly seen through the following reorganized expression for $\mathrm{d}t$:

$$\mathrm{d}t_{it} = \left(\mu_i - 1\right)\frac{dx_{it}}{1-s_{Mi}} + \mu_i du_{it}^V + \mathrm{d}z_{it}^V\,. \tag{7}$$

The 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 share of labor and capital income in aggregate VA, while d*l* and 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:

$$\mathrm{d}x_t^V = \sum_i w_i \mathrm{d}x_{it}^V - R_{L,t} - R_{K,t} \,. \tag{8}$$

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.[51] 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 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 (6) into the definition of aggregate TFP, we derive the following expressions:

$$\mathrm{d}t_t = \mathrm{d}v_t - \mathrm{d}x_t^V = \sum_i w_i \mathrm{d}t_{it} + R_{L,t} + R_{K,t} = \left[\left(\bar{\mu}-1\right)\mathrm{d}x_t^V + \mathrm{d}\bar{u}_t^V + R_{M,t}\right] + R_{\mu,t} + \bar{\mu}\left(R_{L,t} + R_{K,t}\right) + \mathrm{d}z_t^V \,, \tag{9}$$

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 is increasing returns or imperfect competition. R_μ stems from reallocation across firms with different markups.

[51] 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.

dz_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 thus inherit the estimation errors. Alternatively, we can group R_M with the other reallocation terms to form a composite reallocation term, that is:

$$\mathbf{R} = R_{M,t} + R_{\mu,t} + \bar{\mu}\left(R_{L,t} + R_{K,t}\right), \tag{10}$$

Clearly, if μ_i = 1 for all i's, corresponding to no markup, only $R_{L,t} + R_{K,t}$ will remain while 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 $dt_t = d\bar{u}_t^V + dz_t^V$. 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, (9) shows that aggregate TFP growth includes not only technology growth but also contribution from unmeasured inputs and reallocation of resources across firms. It should be informative to examine how much of the declining procyclical of aggregate TFP (and LP) can be attributed 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 on just 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 the true output of a firm V^* (for value added), which includes observed output for current sale in the market place (denoted V) and unobserved output generated by productive activities intended to boost its potential future revenue (denoted U). U can be regarded as unmeasured investment produced in-house. 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 data, observed investment comoves positively with output.[52] Then to a first-order approximation, the relationship in growth rates between V and U can be expressed as (as usual, log differences represent growth rates):

$$\mathrm{d}u = \xi \mathrm{d}v + \mathrm{d}\varepsilon \, , \tag{11}$$

where $\xi = \left(\partial \Xi / \partial V\right)\left(V / \Xi\right)$ 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 be different, we can regard the growth of total output as a Divisia index of observed and unobserved output.[53] Then we have the following expression for the growth rate of observed output $\mathrm{d}v$:

[52] 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 will elaborate further on this assumption in the next section.

[53] Their respective production function 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.

$$\mathrm{d}v = \frac{1}{s_Y + (1 - s_Y)\xi}\left[\mathrm{d}v^* - (1 - s_Y)\mathrm{d}\varepsilon\right], \tag{12}$$

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) and hours per worker (H), and unobserved effort (E): $L^* = (HN)E \equiv LE$ [54] 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 de uncorrelated with observed hours. We assume that $\mathrm{d}\omega$ is also uncorrelated with either dv or dε. Thus any correlation between du and de is fully captured through their comovement with observed output (dv) and labor input (dl), respectively. Combining all the terms, we have the following relationship regarding labor input:

$$\mathrm{d}l = \mathrm{d}l^* - \zeta \mathrm{d}h - \mathrm{d}\omega. \tag{13}$$

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

$$\mathrm{cov}(\mathrm{d}v, \mathrm{d}l) = \frac{1}{\left[s_Y + (1 - s_Y)\xi\right]}\left[\mathrm{cov}(\mathrm{d}v^*, \mathrm{d}l^*) - \zeta\, \mathrm{cov}(\mathrm{d}v^*, \mathrm{d}h)\right]. \tag{14}$$

This in turn implies that the covariance between measured output and labor productivity (da) growth equals:[55]

$$\mathrm{cov}(\mathrm{d}v, \mathrm{d}a) = \mathrm{var}(\mathrm{d}v) - \mathrm{cov}(\mathrm{d}v, \mathrm{d}l) = \frac{\mathrm{var}(\mathrm{d}v^*) + (1 - s_Y)^2\, \mathrm{var}(\mathrm{d}\varepsilon)}{\left[s_Y + (1 - s_Y)\xi\right]^2} - \frac{\mathrm{cov}(\mathrm{d}v^*, \mathrm{d}l^*) - \zeta\, \mathrm{cov}(\mathrm{d}v^*, \mathrm{d}h)}{\left[s_Y + (1 - s_Y)\xi\right]}. \tag{15}$$

If we measure the cycliality of LP by its linear regression coefficient on VA growth, which equals the percent change in LP accompanying a one percent change in VA, then the coefficient estimate $\hat{\beta}$ equals:

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[54] We again ignore labor quality in these derivations because of its small overall contribution to labor input growth. What matters here would be 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.

[55] Note we ignore labor quality (dlq) adjustment. Otherwise, the covariance between output and labor productivity should include an additional term: cov(dv, dlq).

$$\hat{\beta} = 1 - \frac{\operatorname{cov}(\mathrm{d}v, \mathrm{d}l)}{\operatorname{var}(\mathrm{d}v)} = 1 - \frac{\left(1-\hat{\beta}^*\right)\operatorname{var}\left(\mathrm{d}v^*\right) - \zeta \operatorname{cov}\left(\mathrm{d}v^*, \mathrm{d}h\right)}{\left[\operatorname{var}\left(\mathrm{d}v^*\right) + \left(1-s_Y\right)^2 \operatorname{var}(\mathrm{d}\varepsilon)\right] \Big/ \left[s_Y + \left(1-s_Y\right)\xi\right]}. \tag{16}$$

Here we have substituted 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 few 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 (16). 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 the 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:

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

$$\partial\hat{\beta}/\partial\xi < 0, \qquad \text{and } \partial\hat{\beta}/\partial\zeta > 0. \tag{17}$$

For any given s_Y, (17) states that $\hat{\beta}$ would fall with ζ, meaning when 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 when unmeasured output becomes more volatile relative to measured output. The sign of $\partial\hat{\beta}/\partial s_Y$ warrants special attention.[56] It is positive if ξ exceeds 1 by a sufficient margin as spelled out in (17), 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 would fall if the share of business activities devoted to producing market output falls.

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

This is a plausible case when unmeasured output is small relative to measured output, and then 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 rises.

In short, these 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 the 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. A Simple Model of Internal Production of Intangible Capital with Unobserved Utilization

This section solves a simple optimizing model that features measurement errors in both input and output of a firm. The objective is to derive the relationship between observed input and unobserved utilization with the presence of unobserved output, chosen optimally by a firm to maximize shareholder value. The optimality conditions help provide the structure for hypothesizing explanations for the change in the cyclicality of productivity since the mid 1980s. This model can also be used to analyze the relative use of extensive versus intensive margins of labor input when adjustment cost or marginal cost schedule changes, and when demand or technology shocks become more or less persistent.

In terms of unmeasured output, this model considers the production of intangible capital that is later used in producing the firm's market output. This type of output can be broadly construed to encompass all unmeasured research and development (R&D) spending by firms. Here the benefit of such investment is modeled as lowering the cost of the firm's market output in the future for given input prices. It can also be modeled as creating new product varieties. In terms of unmeasured input, the model incorporates unobserved fluctuations in labor effort. Here for clarity we omit explicit consideration of observed variations in capital utilization. But this does not alter the conclusion qualitatively, because Basu and Kimball (1997) have shown that the observed proxy—variation in weekly hours—for unobserved labor effort is also the right proxy for varying capital utilization in the form of overtime wage premium.

Each firm produces two output: a product for sale in the market and the capital used in the production of this market good. Only the market output is measured whereas investment in the internal capital is not. The production of this intangible capital good uses only labor and exhibits decreasing returns to scale. As is customary, we assume a one-period lag in the formation of this capital—investment made in this period become productive in the next period. There is only one type of labor used in producing both output. Firms can adjust labor input along three margins: employment, weekly hours and effort. Total employment and hours are observed but effort is not (at least not to people constructing the statistics). Employment is subject to an adjustment cost whereas weekly hours and effort are not. However, the wage rate is increasing in hours and effort; overtime wage premium is often observed in data.

For simplicity, we assume every firm is a price taker in both the product and the factor markets. Then each firm's objective is to maximize the present discounted value of shareholders' payoff, subject to the constraint of the production technology:

$$V_0 = \max_{\Delta_t, E_t, H_t} \mathbf{E}_0 \left\{ \sum_{t=0}^{\infty} \rho^t \left[P_t Q_t - W_t N_t G\left(H_t, E_t\right) - W_t N_t \Psi\left(\Delta_t / N_t\right) \right] \right\}. \tag{18}$$

Given
$$Q_t = Z_t^Q J_t^{1-\alpha} \left(N_t H_t^Q E_t^Q\right)^{\alpha}, \tag{19}$$

$$J_{t+1} = Y_t + (1-\delta_J) J_t, \tag{20}$$

$$Y_t = Z_t^Y \left(N_t H_t^Y E_t^Y\right)^{\beta}, \text{ with } \beta \in (0, 1), \tag{21}$$

$$H_t = H_t^Q + H_t^Y, \tag{22}$$

$$E_t = \left(E_t^Q H_t^Q + E_t^Y H_t^Y\right) / H_t, \tag{23}$$

and
$$N_{t+1} = \Delta_t + (1-\delta_N) N_t. \tag{24}$$

Q_t is the market good produced and sold in period t. It is assumed to be measured without errors. Its production function is described in (19); for simplicity we assume a constant returns Cobb-Douglas function. J_t is the intangible capital used in producing Q_t. The stock of J_t is formed through the accumulation of investment Y_t, which is produced internally and hence not measured. Its production function, described in (21), involves only labor and exhibits decreasing returns to scale. (20) describes the law of motion for J_t, δ_J being the depreciation rate. Z_t^Q (Z_t^Y) is the factor-augmenting technology for producing Q_t (Y_t).

There is only one type of worker and every worker divides her hours between producing Q_t and Y_t. N_t denotes the overall number of workers , while H_t^Q (H_t^Y) and E_t^Q (E_t^Y) denote the average weekly hours and labor effort used in producing Q_t (Y_t), respectively. W_t in the labor-related cost terms (the second and third terms in the bracket) in (1) denotes the base wage rate. The actual wage rate $W_t G(H_t, E_t H_t)$, however, depends positively on both the average hours and the hours-weighted average effort, meaning the partial derivatives of $G_t \equiv G\left(H_t, E_t\right)$ with respect to H_t (denoted $G_{H,t}$) and E_t (denoted $G_{E,t}$) are both positive. Equation (24) describes the evolution of N_t, with Δ_t being the number of new hires. For simplicity, we assume a constant rate of (voluntary) attrition for

workers, denoted δ_N.[57] The firm has to incur a separate cost Ψ(.) to adjust the number of workers. The overall cost is expressed as a multiple of the basic wage bill W_tN_t. For tractibility, here we only consider a convex adjustment cost. Studies have shown that this is a reasonable formulation at the industry level (Bond and van Reenen 2007, for example, refer repeatedly to smoothing of adjustment dynamics due to aggregation).

Plugging (19) through (23) into (18), and denoting the multiplier for (24) as λ_t (which is also the present discounted shadow value of an additional worker available for production in period t), we obtain first order conditions (FOCs) with respect to H_t^Q, E_t^Q, H_t^Y, E_t^Y, Δ_t and N_t:

$$\mathbf{E}_0\left\{\rho^t\left[P_t\alpha Q_t / H_t^Q - W_tN_t\left(G_{H,t} + G_{E,t}\left(E_t^Q - E_t\right)/H_t\right)\right]\right\} = 0, \tag{25}$$

$$\mathbf{E}_0\left\{\rho^t\left[P_t\alpha Q_t / E_t^Q - W_tN_tG_{E,t}H_t^Q/H_t\right]\right\} = 0, \tag{26}$$

$$\mathbf{E}_0\left\{\rho^{t+1}\left[P_{t+1}(1-\alpha)\left(Q_{t+1}/J_{t+1}\right)\left(\beta Y_t/H_t^Y\right)\right] - \rho^tW_tN_t\left(G_{H,t} + G_{E,t}\left(E_t^Y - E_t\right)/H_t\right)\right\} = 0, \tag{27}$$

$$\mathbf{E}_0\left\{\rho^{t+1}\left[P_{t+1}(1-\alpha)\left(Q_{t+1}/J_{t+1}\right)\left(\beta Y_t/E_t^Y\right)\right] - \rho^tW_tN_tG_{E,t}H_t^Y/H_t\right\} = 0, \tag{28}$$

$$\lambda_{t+1} = \mathbf{E}_0\left\{\rho^tW_t\Psi_t'\right\}, \tag{29}$$

$$\lambda_t = \mathbf{E}_0\left\{\rho^{t+1}\left[P_{t+1}(1-\alpha)\frac{Q_{t+1}}{J_{t+1}}\frac{\beta Y_t}{N_t}\right] + \rho^t\left[P_t\alpha\frac{Q_t}{N_t} - W_tG_t - W_t\Psi_t\left(1-\Xi_t\right)\right]\right\} + \left(1-\delta_N\right)\lambda_{t+1}. \tag{30}$$

Equation (24) reproduces the FOC with respect to λ_t. As noted above, $G_{x,t}$ denotes the partial derivatives of $G(H_t, E_t)$ with respect to x, where $x = H$ and E. Ξ_t denotes the elasticity of Ψ_t with respect to Δ_t/N_t.

Since the elasticity of benefits with respect to H_t^Q and E_t^Q are the same, so should the elasticity of cost $G(H_t, E_t)$ with respect to the two components of labor input. This condition can be derived by combining intratemporal conditions (25) and (26). It turns out to yield an equality between the elasticity of $G(H_t, E_t)$ with respect to overall average hours H_t (on the left hand side) and its elasticity with respect to the weighted average effort E_t put into producing both goods (on the right hand side):

[57] Δ_t is better construed as the number of workers hired net of those fired. So here the adjustment cost is assumed to depend on net adjustment initiated by the firm. Allowing the cost to depend on both hiring and firing would complicate the exact solution without changing the qualitative result regarding measurement.

$$\frac{G_{H,t}H_t}{G_t} = \frac{G_{E,t}E_t}{G_t}. \tag{31}$$

This is because a marginal increase in H_t^Q affects the wage rate not only by increasing average hours but also by altering (the share of H_t^Q in average hours and hence) the average effort. The latter effect is proportional to $\left(E_t^Q - E_t\right)/H_t$ (as shown in (25)), and the E_t^Q-related part is offset by the marginal effect of an increase in E_t^Q. Condition (31) is identical to equation (13) in Basu and Kimball (1997), even though there is only a single product in their model. They derived the equation under the weaker assumption of cost minimization, which permits any model of firm (pricing) behavior in product markets (as well as increasing returns to scale). They also used a more general functional form for the production function (generalized Cobb-Douglas specifically).

Here we choose to derive (31) from value maximization because we want to show that an identical relationship is obtained for inputs whose marginal value will be realized only in the future. Specifically, an equation identical to (31) also emerges from the FOCs (27) and (28) for H_t^Y and E_t^Y, respectively, even though the intangible capital investment will only bear fruit starting the next period (equal to the capital's expected marginal revenue product in the next period, which in turn depends on the expected price for the firm's market product). This is because the optimal relationship between H_t^Y and E_t^Y is determined by the production function for Y_t, which is produced this period, even though the level of both depends on expected future payoff as well.

To see what (31) implies about the relationship between effort and hours growth, we fully differentiate with respect to H_t^i and E_t^i, with $i = Q, Y$. To streamline the resulting equation, we make use of the familiar relationship that the growth rate of overall average hours H_t is the weighted average of growth rates of hours allocated to producing Q_t and Y_t, with dx denoting the growth rate of variable X (that is, $\mathrm{d}x \equiv \mathrm{d}X/X$):

$$\mathrm{d}h_t = \frac{H_t^Q}{H_t}\mathrm{d}h_t^Q + \frac{H_t^Y}{H_t}\mathrm{d}h_t^Y \equiv s_{H,t}^Q \mathrm{d}h_t^Q + s_{H,t}^Y \mathrm{d}h_t^Y, \text{ with } s_{H,t}^Q + s_{H,t}^Y = 1, \tag{32}$$

The growth rate of overall average effort E_t, however, depends on not only the weighted average growth of the two effort levels but also the relative change in their shares, which depends on the relative change in the two corresponding average hours:

$$\mathrm{d}e_t = \sum_{i=Q,Y}\left[\frac{E_t^i H_t^i}{E_t H_t}\mathrm{d}e_t^i + \left(\frac{E_t^i H_t^i}{E_t H_t} - \frac{H_t^i}{H_t}\right)\mathrm{d}h_t^i\right] \equiv \sum_{i=Q,Y}\left[s_{EH,t}^i \mathrm{d}e_t^i + \left(s_{EH,t}^i - s_{H,t}^i\right)\mathrm{d}h_t^i\right], \text{ with } s_{EH,t}^Q + s_{EH,t}^Y = 1. \tag{33}$$

It is easier to see the intuition of the formula if we rearrange terms and express $\mathrm{d}e_t$ instead as:

$$\mathrm{d}e_t = \sum_{i=Q,Y} s^i_{EH,t}\mathrm{d}e^i_t + \left(s^Q_{EH,t} - s^Q_{H,t}\right)\left(\mathrm{d}h^Q_t - \mathrm{d}h^Y_t\right).$$

$s^Q_{EH,t} > s^Q_{H,t}$ is equivalent to $E^Q_t > E^Y_t$ and vice versa. Hence, the intuition for the hours-related terms for cis that when average hours associated with the higher effort level grows faster, overall average effort level E_t rises as well, and vice versa, even without any change to either effort level E^Q_t or E^Y_t. $\mathrm{d}e_t$ simplifies to depend only on changes in effort levels E^Q_t and E^Y_t when $E^Q_t = E^Y_t$. However, it is not necessary that $E^Q_t = E^Y_t$, as will be shown below.

Denoting ln$G$ = Φ(ln$H$, ln$E$) and using subscripts to denote partial derivatives (evaluated at time t level of inputs), we derive the full differentiation of (31) as follows:

$$\left(\Phi_{EE,t} - \Phi_{HE,t}\right)\sum_{i=Q,Y}\left[s^i_{EH,t}\mathrm{d}e^i_t + \left(s^i_{EH,t} - s^i_{H,t}\right)\mathrm{d}h^i_t\right] = \left(\Phi_{HH,t} - \Phi_{HE,t}\right)\left(s^Q_{H,t}\mathrm{d}h^Q_t + s^Y_{H,t}\mathrm{d}h^Y_t\right). \quad (34)$$

This immediately leads to the following intuitive relationship between de and dh:

$$\mathrm{d}e_t = \frac{\Phi_{HH,t} - \Phi_{HE,t}}{\Phi_{EE,t} - \Phi_{HE,t}}\mathrm{d}h_t \equiv \nabla_{HE,t}\mathrm{d}h_t. \quad (35)$$

To determine the sign of ∇_{HE}, we adopt the assumptions in Basu and Kimball (1997) regarding the cost function $G(H_t, E_t)$ (and hence Φ(.,.)): G(.,.) is convex and satisfies two conditions for the second derivatives: $\Phi_{HH} > \Phi_{HE}$ and $\Phi_{EE} > \Phi_{EH}$.[58] Then clearly $\nabla_{HE} > 0$. This means that de and dh always move in the same direction. In other words, the firm always adjusts average hours and effort in the same direction, resulting in a monotonically increasing relationship between average hours H_t and effort E_t:

$$E_t = \mathrm{E}\left(H_t\right), \text{ with } \mathrm{E}'(.) > 0. \quad (36)$$

This result is intuitive in that the cost function $G(H, E)$ is convex in both overall average hours and effort H and E, but not necessarily on either component of each respective input. This further implies that the monotonic relationship between H_t and E_t does not necessarily extend to their respective components, meaning it is possible for H^Q_t (H^Y_t) and E^Q_t (E^Y_t) not to comove. For instance, if $E^Q_t > E^Y_t$ and a shock (such as a one-time positive impulse to Z^Q_t) causes the firm to increase H^Q_t, which clearly raises H_t, this leads E_t to rise as well even without any change to E^Q_t. Depending on parameter values, this may be sufficient to satisfy (34). Inspection of (34) indicates

[58] Specifically, $G(H_t, E_t)$ being convex ensures a global optimum. Assuming $\Phi_{HH} > \Phi_{HE}$ and $\Phi_{EE} > \Phi_{EH}$ means it is more expensive to increase one input only than to increase hours and effort jointly.

that either effort E_t^i (i = Q or Y) has to move in the same direction as hours H_t^i when the latter's change shifts E_t in the opposite direction (for instance, H_t^Q falls and lowers E_t in the above example). To obtain more specific relationships among individual components of hours and effort, we need further assumptions about the second derivatives Φ_{ij} (i, j = H or E).

The measurement implication of (36) is that we can use the observed variable—average hours H_t—as a proxy for the unobserved variable of the average effort E_t. This is convenient because we invariably observe just the overall average weekly hours spent on all activities carried out by firms but hardly ever the separate hours spent on different activities, such as on producing Q_t versus Y_t in this model. Hence, even if a monotonically increasing relationship between hours and effort for an individual activity were known, detailed data are generally unavailable to adjust for the corresponding effort level separately.

In contrast, (36) is silent about whether the growth of measured output Q_t can serve as a valid proxy for the growth of unobserved output Y_t. Additional assumptions are needed. It seem reasonable, for example, to assume that unobserved investment is combined with purchased capital goods to produce installed capital that enter the production function. A chosen aggregator function for capital will then imply specific relationship between unmeasured and measured investment. This is the approach taken in BFOS (2004).

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 Private Nonfarm Industries, 1950-2007

VARIABLES	(1) **N**	(2) **Mean**	(3) **S.D.**	(4) **Min**	(5) **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 to 2007, all in percent, for the 27 private nonfarm industries used in the industry-level analysis. The factor shares are all as percent 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 private nonfarm industries in total VA of all industries

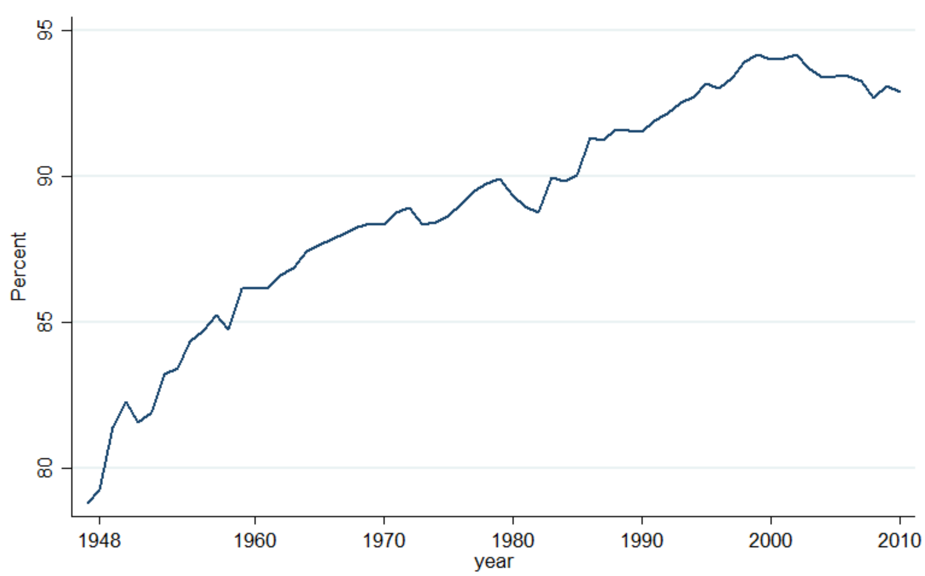

Table B.3 Responses of output and inputs to technology shocks: before 1984 and the change afterward
(based on unconstrained production function coefficients reported in Table 8a)

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}	0.185	-0.00579	-0.108	0.0721	**-0.168*** **	**-0.753*** **	**0.191** **	0.294***	-0.142
	[0.158]	[0.142]	[0.183]	[0.153]	**[0.0257]**	**[0.0886]**	**[0.0805]**	[0.0997]	[0.0979]
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}	0.00669	-0.0616	-0.170	-0.133	**-0.0106**	**0.130**	**0.0678**	0.176*	-0.177*
	[0.152]	[0.137]	[0.176]	[0.147]	**[0.0247]**	**[0.0853]**	**[0.0775]**	[0.0960]	[0.0943]
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}	0.189	0.115	0.0629	0.0277	**0.0643** **	**0.233*** **	**0.0742**	0.126	-0.217**
	[0.161]	[0.145]	[0.186]	[0.156]	**[0.0262]**	**[0.0904]**	**[0.0821]**	[0.102]	[0.0999]
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}	0.0264	0.0659	-0.0112	0.0258	**0.0177**	**-0.0274**	**-0.0394**	0.0376	-0.0813
	[0.174]	[0.157]	[0.202]	[0.168]	**[0.0283]**	**[0.0978]**	**[0.0888]**	[0.110]	[0.108]
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}	-0.0198	-0.106	-0.161	-0.120	**0.0138**	**0.0653**	**0.0856**	0.141	-0.0592
	[0.163]	[0.147]	[0.189]	[0.157]	**[0.0265]**	**[0.0915]**	**[0.0831]**	[0.103]	[0.101]
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]
σ*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
Chi-squared	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.