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of labor productivity

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# Industry evidence and the vanishing cyclicality of labor productivity *

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**Abstract**

Aggregate labor productivity used to be strongly procyclical in the United States, but the procyclicality has largely disappeared since the mid-1980s. This paper explores the industry-level evidence in order to discriminate between existing explanations of the vanishing procyclicality of the labor productivity.

I document the change in the cyclical properties of productivity in the U.S. using industry-level data and focus on a particularly puzzling feature, namely that the correlations of the industry productivity with industry output and labor input remained on average much more stable before and after the mid-1980s compared to the aggregate correlations. In other words, there is little evidence for the vanishing cyclicality of labor productivity at the industry level.

I construct a simple industry-level RBC model that nests two leading explanations of the vanishing cyclicality of productivity that have been proposed in the literature. I show that the two explanations have qualitatively different predictions for the cyclical properties of industry-level variables. The mechanism based on a structural change in the composition of aggregate shocks is able to replicate the stability of industry-level moments across time. In contrast, the mechanism based on increased labor market flexibility is less successful in matching the industry-level evidence.

**Keywords:** business cycles, productivity, industries, factor utilization, Great Moderation

**JEL Classification Numbers:** E32, E24, E37

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# 1 Introduction

Macroeconomists tend to think about business cycle fluctuations in terms of fixed relationships that generate stable co-movement patterns between economic variables. However, the nature of business cycle fluctuations in the U.S. have changed over the last 70 years. The procyclicality of aggregate labor productivity used to belong to the most strongly documented stylized facts in macroeconomics, but recent studies show it has largely disappeared.

In the 1980s, the robust empirical evidence on procyclical productivity actually led to the emergence of the real business cycle theory, in which the fluctuations of productivity are the driving force behind business cycles. The concept of productivity fluctuations as one of the driving forces behind macroeconomic fluctuations still continues to be influential in both academic and applied economics today.

However, more recent literature, including e.g. Stiroh (2009) and Galí and Gambetti (2009), pointed out that the procyclicality of measured aggregate productivity has largely disappeared since the mid-1980s. This observation challenges the validity of business cycle models based on the exogenous fluctuations of productivity, and more generally the validity of macroeconomic models which generate procyclical productivity exogenously or endogenously. Finding a sound explanation of the change in the co-movement patterns is of crucial importance for the correct identification of sources of business cycle fluctuations, and thus has implications for economic theory and policy. Numerous potential explanations of the vanishing procyclicality of productivity have been proposed in the macroeconomic literature, ranging from changes in cyclical measurement errors of production inputs and outputs (e.g. Galí and van Rens 2019, Berger 2018, Garin et al. 2018, Nucci and Riggi 2013, and McGrattan and Prescott 2010) to structural changes in composition of shocks and their effects on the economy (e.g. Galí and Gambetti 2009, Barnichon 2010, and Yépez 2017).

In this paper I contribute to the discussion by bringing in industry-level evidence, which I argue can help to discriminate between various explanations of the vanishing procyclicality of labor productivity. I first document the change in cyclical properties of productivity in the U.S. using industry-level data, which to my knowledge was only previously considered by Wang (2014). I use the dataset constructed by Dale Jorgenson and his co-authors (Jorgenson, 2008), which contains information about the U.S. economy between 1960 and 2005 disaggregated into 88 industries. My empirical observations are broadly in line with Wang (2014) but my focus is on documenting a particularly puzzling feature of the industry-level data: the correlations of industry productivity with industry output and labor input remained on average much more stable before and after the mid-1980s compared to the aggregate correlations. In other words, there is little evidence for vanishing pro-cyclicality of labor productivity at the industry level. At the same time, the change in composition of industries explains only a small part of the reduction of procyclicality of measured productivity. Instead, the majority of the decrease in correlations between aggregate productivity and output (resp. hours) can be attributed to the change in co-movement across industries.

After establishing these empirical observations I construct a simple industry-level RBC model that nests several explanations of the vanishing cyclicality of productivity proposed in the literature. I use the model to evaluate whether the proposed mechanisms are compatible with the industry-level evidence. Despite its simplicity, the model can qualitatively replicate the changes in the cyclical co-movement of measured aggregate productivity and other macroeconomic variables through two distinct mechanisms. The procyclicality of aggregate productivity in the model, measured in terms of correlations with labor input and output, decreases when the relative size of aggregate demand side shocks decreases compared to technology shocks, as suggested e.g., in Barnichon (2010). The procyclicality of aggregate productivity also decreases when the observed labor input (hours) becomes more flexible in comparison to the unobserved labor input margin (effort), as suggested in, for example, Galí and van Rens (2019).

Although both mechanisms are able to reduce the correlations of aggregate productivity with output and labor input, I show that they have qualitatively different predictions for the cyclical properties of industry-level variables. Within my model framework, the mechanism based on a structural change in the composition of aggregate shocks is able to replicate the stability of industry-level moments across time. In contrast, the mechanism based on a change in the flexibility of hours is less successful in matching the industry-level evidence.

It is important to mention that the change in the cyclical properties of labor productivity did not appear in isolation. Other potentially related changes appeared roughly at the same time, in the period referred to as the Great Moderation. The volatility of both aggregate output and labor input decreased in mid-1980s (McConnell and Perez-Quiros, 2000), while the relative volatility of aggregate hours compared to output increased (Galí and Gambetti, 2009). The recoveries during the last three decades were untypically slow (Galí et al., 2012). In addition, there is some discussion on whether the lead-lag structure of employment and output has changed. After the three most recent recessions, some studies argued that in comparison to output, it took a relatively long time for employment to start recovering, an observation referred to as jobless recoveries; see e.g. Bernanke (2009), Jaimovich and Siu (2012), Berger (2018).

The rest of this paper is organized as follows: in the remainder of this section, I describe the relationship of the paper to the existing literature. I present the empirical findings in section 2. Section 3 describes the model. In section 4 I present the quantitative results and discuss the intuition behind these results in sections 5 and 6. Section 7 concludes.

## 1.1 Relationship to the existing literature

The analysis in this paper complements the extensive body of theoretical and empirical literature on change in cyclicality of U.S. labor productivity starting from Stiroh (2009) and Galí and Gambetti (2009). The previous studies have documented a robust decline in correlations between measured aggregate productivity and aggregate output, resp. production inputs across the two time periods: first, the post-war period between 1950 and mid-1980s which I refer to as *pre-1984* period and second, the *post-1984* period from 1984 to up to 2015, where the end date depends on data availability.[1] Extensive empirical analyses have been conducted by Fernald and Wang (2016), Wang (2014), and Daly et al. (2017) among others.

[1] I choose the breaking point between the two sub-periods in line with the rest of the literature to be the beginning of 1984.

Fernald and Wang (2016) provide an overview of the existing explanations of vanishing cyclicality of productivity and analyse the empirical evidence related to a wide range of these explanations. They make several important points based on the quarterly U.S. data series developed by Fernald (2014). Using the identification strategy based on Basu et al. (2006), Fernald decomposes the measured productivity series into *factor utilization* component and *utilization-adjusted TFP*, a purified measure of productivity which in theory more closely reflects the true technological progress. Fernald and Wang (2016) find that (1) utilization-adjusted TFP was never really pro-cyclical before the mid-1980s, and it remained so,[2] (2) factor utilization was the procyclical component of measured productivity before the mid-1980s and it stayed procyclical,[3] and (3) the relative volatility of factor utilization compared to utilization-adjusted TFP substantially decreased in the period after 1984. The major part of the drop in cyclicality of measured productivity is explained by the decrease in volatility of the utilization component. Fernald and Wang stress that any theory aspiring to explain the vanishing procyclicality of aggregate productivity must necessarily be consistent with these three observations.

Wang (2014) is, to my knowledge, the only other paper analysing the industry-level evidence on vanishing cyclicality of productivity. Wang uses an alternative data set, 31 industry U.S. data published by World KLEMS (2010). The moment statistics reported by Wang are consistent with my own computations, however, the interpretation of the observed facts differs in some cases. Most noticeably, I stress that the correlations of industry-level productivity with industry-level output and labor input remained on average much more stable between and after 1984 compared to the aggregate correlations. Indeed, Wang (2014) also decomposes the aggregate correlations into the contribution of within-industry and cross-industry correlations and finds that the vast majority of actual change in the aggregate correlations comes from the cross-industry terms. She subsequently normalizes the contribution of the cross-industry terms by the disproportionally high number of cross-industry pairs and concludes that per industry pair, the contribution of within-industry changes is more important. I argue in this paper that there is no theoretical justification for such normalization and provide a model that illustrates the relationship between the industry-level and aggregate correlations from a new perspective.

I loosely follow Fernald and Wang (2016) in classifying the explanations proposed in the literature into mechanisms based on (1) systematic measurement errors of inputs or outputs and (2) other structural explanations.

The first group of explanations is based on some kind of cyclical measurement error of inputs or outputs. There would be no change in cyclicality of measured productivity if all the inputs and outputs were exactly accounted for. The mechanism that has attracted perhaps the most attention is based on the change in the efficiency of labor markets. Galí and van Rens (2019) argue that an improvement in the labor market matching technology effectively made adjusting the labor force less costly, which made firms rely less on adjusting unobservable intensive margins of production (such as labor utilization in form of unobserved labor effort, imperfectly measured overtime hours, or capital utilization) and more on adjusting the number of employees.[4] Galí

[2]If anything, utilization-adjusted TFP became more correlated with inputs and outputs after the mid-1980s, not less correlated.

[3]The correlation of the utilization measure with labor input actually decreased for brief periods between 1990 and 2005, but the effect is less important than the drop in the volatility of factor utilization component.

[4]The idea goes back to a literature, starting with Oi (1962) and Solow (1964), which attributes the procycli-

and van Rens stress that this mechanism is simultaneously able to explain another change in the nature of macroeconomic fluctuations, namely the increase in relative volatility of aggregate hours compared to aggregate output. The basic idea behind the mechanism, which I also integrate into the model and explore in this paper, is described in Galí and van Rens (2019, pages 2-3) as follows:

Suppose that firms have two margins for adjusting their effective labor input: (observed) employment and (unobserved) effort, which are denoted (in logs) by $n$ and $e$, respectively.[5] Both margins of labor input are transformed into output according to a standard production function,

$$y = (1 - \alpha)(n + e) + a, \tag{1}$$

where $a$ is log total factor productivity and $\alpha$ is a parameter measuring diminishing returns to labor. Measured labor productivity, or output per worker, is given by

$$y - n = -\alpha n + (1 - \alpha)e + a. \tag{2}$$

Labor market frictions make it costly to adjust employment $n$. Since these adjustment costs are convex, frictions are higher when the average level of hiring is higher. Effort provides an alternative margin of adjustment of labor input and is not subject to those frictions (or to a lesser degree). Thus, the larger the frictions, the less employment fluctuates and the more volatile are fluctuations in effort. Reduced hiring frictions decrease the volatility of effort and therefore increase the relative volatility of employment with respect to output. The increased volatility of $n$ also makes labor productivity less procyclical, and, in the presence of shocks other than shifts in technology, may even make productivity countercyclical.

Other papers featuring similar mechanisms include Barnichon (2010), Lewis et al. (2018), Evans (2019) and Nucci and Riggi (2013). An alternative channel through which higher flexibility in the labor markets may have played a role is that firms might be able to better identify less productive workers and lay them off more selectively during bad times. Berger (2018) suggests that this can explain both the good performance of labor productivity in recessions and the slow recovery of employment afterwards. Although there is no unmeasured labor input margin present in this mechanism, the heterogeneous workers' quality creates a wedge between observed and effective labor input. The implications from my model can not directly speak to the mechanism proposed by Berger, but it is likely that increased selective hiring, similar to other explanations based on the labor market flexibility, would also generate substantial changes at the industry level. Riggi (2019) proposes another alternative mechanism based on efficiency wages that is able to generate countercyclical work effort if firms imperfectly detect shirking workers. An improvement in monitoring possibilities of firms in her model can generate a decrease in the correlation between measured productivity and labor input. However, the volatility of labor utilization in this case increases, which is not in line with the observations made by Fernald and Wang (2016).

Another idea connected to the systematic measurement errors that my model does not

cality of productivity to variations in effort, resulting in seemingly increasing returns to labor.

[5]To simplify the argument, we assume hours per worker are constant, consistent with the observation that in the US data most adjustments in total hours worked take place along the extensive margin.

directly address is that the growing importance of intangible investment might have led to systematic errors in measurement of output; see McGrattan and Prescott (2010), McGrattan (2017). To the extent that intangible investment activity is procyclical, measured productivity may have become less correlated with measured output if intangible output became more important.

However, the higher share of unmeasured intangible investment in output also does not explain why the volatility of the factor utilization component constructed by Fernald (2014) became less volatile compared to the utility-adjusted TFP. The factor utilization component is identified based on the fluctuations of observed hours per worker, a margin that is not directly affected by the share of intangible investment. Thus, the mechanism is not in line with the empirical observations made by Fernald and Wang (2016). Moreover, Wang (2014) uses the observed intensity of ICT-investment at industry level as a proxy for the intangible investment, assuming complementarity between the two margins. Wang finds little evidence that intangible investment explains the decline in cyclicality of measured productivity. Nevertheless, one must stress that assessing the role of intangible investment inherently suffers from data limitations, as intangible investment activities are hard to measure. McGrattan (2017) makes a considerable contribution in this respect by improving the existing industry-level datasets to better reflect the increasing importance of intangible investment.

A further mechanism that gives rise to a wedge between measured and actual productivity at aggregate and industry level is reallocation. Garin et al. (2018) suggest that procyclical reallocation became much more prominent since the mid-1980s due to the increased importance of industry-specific shocks documented, for example, by Foerster et al. (2011). Although I also analyse the role of changing importance of aggregate shocks, my model does not feature any reallocation friction. Fernald and Wang (2016) argue that the reallocation component also does not enter the factor utilisation term, making it an unlikely main driver of vanishing cyclicality of aggregate labor productivity. However, this mechanism could have contributed to the observed changes.

Lastly, it is clear that the U.S. economy has undergone substantial changes in composition over the last 70 years. Carvalho and Gabaix (2013) have argued that a substantial part of the decrease in variance of macroeconomic variables in the Great Moderation can be explained by the changes in composition of industries. However, in line with Wang (2014) I show in section 2 that the changes in composition only explain a minor part of the observed change in cyclicality of measured productivity.

The second broad group of explanations has related the observed changes in the cyclical behaviour of macroeconomic variables more directly to structural changes. These include changes in relative importance of various types of shocks, or the way in which the shocks affect the economy.

Numerous studies have identified a change in the size and composition of different types of shocks after the mid-1980s. Some authors argued that the Great Moderation can be accounted to good luck (Justiniano and Primiceri 2008, Arias et al. 2007). Others have attributed the changes to a different policy conduct or changing structure of the economy in general; see e.g. Clarida et al. (2000), Kahn et al. (2002), Galí and Gambetti (2009), Dynan et al. (2006), Yépez

(2017).

Barnichon (2010) and Galí and Gambetti (2009) connect the vanishing cyclicality of productivity to the observation that aggregate demand shocks have become less volatile relative to aggregate technology shocks after the mid-1980s. Different types of shocks, for example technology or monetary policy shocks, naturally affect the measured productivity differently. Because the responses of macroeconomic variables to various shocks depend on the model framework, the effect of changes in shock composition on the cyclicality of productivity can only be studied within a given model. Both empirically and within a typical New-Keynesian model framework, technology improvements raise the measured productivity but cause hours to contract in the short run; see e.g. Galí (1999). Therefore, greater importance of technology shocks implies that the share of utilization-adjusted TFP in the measured productivity grows and, simultaneously, that the correlation of measured productivity with inputs decreases. This is also the case in my model, which features both demand side and technology aggregate shocks.

In the remainder of this paper, I concentrate on the two most prominent mechanisms from both strands of the literature, the labor market flexibility explanation and the shock composition explanation. I build an industry-level model that, in a simple form, nests the mechanisms from Galí and van Rens (2019) and Barnichon (2010). I replicate the aggregate implications of these papers and compare their industry-level predictions with the evidence.

In order to keep the main insights of my paper intuitive and tractable, I keep the industry structure of the economy as simple as possible. I abstract from using the realistic industry composition and the input-output linkages between industries. Nevertheless, it is important to mention that this simplification is not completely innocuous. A rich literature documents the important role of industry structure and the input-output linkages for generating realistic co-movement patterns between the industry-level economic variables; see e.g. Horvath (2000), Dupor (1999), Acemoglu et al. (2012), Holly and Petrella (2012), Atalay (2017). The industry structure also influences the extent to which industry-specific shocks propagate across industries, and therefore determines the relative importance of aggregate and industry-specific shocks necessary to generate the realistic economic fluctuations at both the industry and aggregate level. For this reason, my model is not able to generate the realistic co-movement patterns observed across industries in the U.S. economy. Moreover, the importance of industry-specific shocks in generating aggregate fluctuations might be underestimated in my model.

# 2 Empirical evidence: Changes in cyclicality of productivity at the aggregate and industry level

In this section I present the empirical evidence on the change in cyclicality of measured productivity and other macroeconomic variables in the U.S. in the periods before and after 1984. I first introduce the data source and show that the aggregate moments constructed using the data are consistent with the findings in the existing literature. I then continue by analysing the industry-level evidence. I find that the industry-level correlations remained on average much more stable across the two time periods compared to the aggregate correlations. I analyse the effect of industry composition and find that it only contributed a minor part of the observed changes of aggregate correlations. In order to shed more light on these seemingly inconsistent industry-level observations I decompose the aggregate correlations into the contribution of within-industry and cross-industry correlations and find that the vast majority of the actual change in aggregate correlations comes from decreased co-movement across industries.

## 2.1 Data

The primary data source that I use is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson 2008). The data set provides annual information on capital, labor and intermediate inputs and outputs of the U.S. economy between 1960 and 2005 disaggregated into 88 industries. Most of the literature so far has focused on analysing aggregate-level data, such as from the BLS Labor Productivity and Cost (LPC) program, which are available at higher frequency, but do not contain industry-level information. In line with the literature I focus on the private business sector which consists of 77 industries.

I use the standard bottom-up KLEMS methodology in order to construct the aggregate series from the industry-level data; see e.g. Timmer et al. (2007). I also rely on the KLEMS methodology for computing the two standard measures of productivity: labor productivity and total factor productivity (TFP). I thus define the measured labor productivity as value added per effective hour and measured TFP as the usual Solow residual.[6] While most of the existing literature reports results for both measured labor productivity and TFP, Wang (2014) argues for focusing on TFP as a cleaner measure of productivity.

The measure of labor input reported in Jorgenson's dataset is effective hours. Effective hours are defined as total hours adjusted for the composition of the workforce, taking into account some observable characteristics (education, age and gender). The details describing the construction of data series and the moments are provided in Appendix A.

## 2.2 Change in cyclicality of aggregate productivity

Previous literature has documented significant differences in cyclicality of productivity in the U.S. between periods pre- and post-1984. The correlation of measured aggregate labor productivity with output went from strongly procyclical to acyclical, while correlation of measured aggregate labor productivity with labor input went from weakly procyclical to countercyclical. The aggregate stylized facts computed from the industry-level Jorgenson data set are consistent with these observations: various measures of cyclicality of aggregate productivity have substantially decreased since the mid-1980s. Figure 1 plots the annual growth rates of aggregate value added, hours, and labor productivity constructed from the Jorgenson data.

To document the aggregate changes, I compute four correlations: between measured aggregate labor productivity ($LP$) resp. total factor productivity ($TFP$) and aggregate value added ($VA$) resp. hours ($H$). I compute each of the correlations using four different detrending methods. I use growth rates (first differences), Christiano-Fitzgerald band-pass filter that isolates the frequencies between 2 and 8 years, and Hodrick-Prescott filter with smoothing parameters

[6] My measure of TFP at both aggregate and industry level is value added-based, not gross output-based Solow residual. The difference between the two measures only affects the scaling of the productivity series.

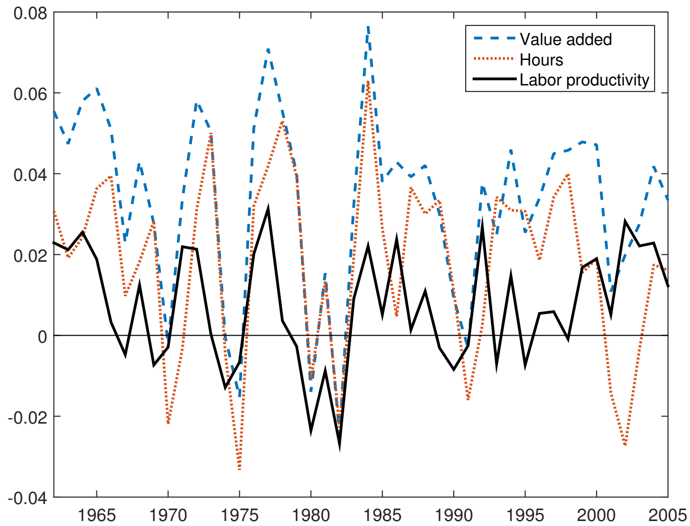


Figure 1: Aggregate variables constructed from industry-level Jorgenson (2008) data set: annual growth rates of value added, hours, and labor productivity.

$\lambda = 100$, resp. $\lambda = 6.25$.[7]

Table 1 reports the cyclical correlations for the two time periods of interest. The correlation of measured aggregate labor productivity with hours decreased sharply from weakly procyclical to strongly countercyclical, with the difference between the two sub-periods ranging from $-0.58$ to $-0.85$ depending on the detrending method. The correlation of labor productivity with output decreased from procyclical to basically acyclical, with the difference ranging between $-0.29$ and $-0.58$. The table also shows that measured TFP is consistently more procyclical than labor productivity. This is not surprising, as capital is relatively rigid compared to labor input and capital intensity is thus countercyclical. The important observation is that even though measured TFP is in general more procyclical than labor productivity, its cyclicality also decreased substantially between the two sub-periods, and the magnitude of the change is comparable with the cyclicality of labor productivity.

The correlations are qualitatively in line with the previous literature. Correlations of productivity measures with output are directly comparable to Wang (2014), who also uses annual industry-level data set to construct the moments. Correlations are quantitatively in line with Wang for most of the filtering methods, with minor differences attributable to the difference in the sample lengths. The comparison of my results with the correlations reported in Wang (2014) and the correlations based on quarterly aggregate data reported by Galí and van Rens (2019) is provided in Appendix B.

I omit the computation of standard errors for the aggregate second moments. The statistical significance of the observed changes has been tested multiple times by the previous studies using the quarterly data. The annual data set I work with contains fewer observations, hence the statistical significance at the aggregate level is weaker. However, the purpose of this exercise is to confirm the consistency with the existing empirical observations, not to provide new evidence on changing aggregate correlations.

Table 2 reports another important set of moments, standard deviations and relative standard

[7]Both values of the smoothing parameter have been used in the literature to which I relate.

| | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| **corr(TFP, VA)** | | | | |
| First Diff. | 0.72 | 0.85 | 0.46 | -0.39 |
| CF | 0.82 | 0.85 | 0.70 | -0.14 |
| HP par=100 | 0.68 | 0.86 | 0.15 | -0.71 |
| HP par=6.25 | 0.76 | 0.85 | 0.40 | -0.45 |
| **corr(TFP, H)** | | | | |
| First Diff. | 0.22 | 0.52 | -0.27 | -0.79 |
| CF | 0.45 | 0.56 | 0.08 | -0.48 |
| HP par=100 | 0.23 | 0.61 | -0.46 | -1.06 |
| HP par=6.25 | 0.37 | 0.60 | -0.26 | -0.86 |
| **corr(LP, VA)** | | | | |
| First Diff. | 0.32 | 0.49 | 0.11 | -0.37 |
| CF | 0.40 | 0.49 | 0.20 | -0.29 |
| HP par=100 | 0.31 | 0.57 | -0.01 | -0.58 |
| HP par=6.25 | 0.29 | 0.47 | -0.03 | -0.50 |
| **corr(LP, H)** | | | | |
| First Diff. | -0.29 | 0.04 | -0.63 | -0.66 |
| CF | -0.10 | 0.10 | -0.49 | -0.58 |
| HP par=100 | -0.23 | 0.20 | -0.64 | -0.85 |
| HP par=6.25 | -0.21 | 0.11 | -0.67 | -0.78 |

Table 1: Cyclical correlations between selected productivity measures and output, resp. hours. Comparison pre- and post-1984. Each correlation is computed using four different detrending methods.

| **Standard deviation** | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| Value added ($VA$) | 2.25 | 2.73 | 1.62 | -1.12 |
| Hours ($H$) | 2.23 | 2.39 | 2.06 | -0.33 |
| std($H$)/ std($VA$) | 0.99 | 0.87 | 1.27 | 0.40 |
| std($TFP$)/ std($VA$) | 0.63 | 0.58 | 0.71 | 0.13 |

Table 2: Volatility (in percent) and relative volatility of selected aggregate variables. Comparison pre- and post-1984. Moments computed for growth rates of the variables.

deviations of selected aggregate variables, reported for the growth rates. In line with the existing literature I find that while both volatility of output and hours has decreased, the relative volatility of aggregate hours compared to output has increased between the two sub-periods. The comparison with the moments reported in Galí and van Rens (2019), as well as results for other detrending methods, are provided in Appendix B.

### 2.3 Industry evidence

This section reports the moments at the industry level. Table 3 displays the correlations analogous to table 1, but instead of aggregate correlations it displays weighted averages across the 77 industry-level correlations. The correlations are weighted by industry nominal output shares in the pre-1984 period. However, the results reported in table 3 are robust with respect to alternative choices of weights.

The industry-level results in table 3 differ qualitatively from the patterns observed for the

| | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| **corr(TFP, VA)** | | | | |
| First Diff. | 0.80 | 0.81 | 0.79 | -0.02 |
| CF | 0.82 | 0.81 | 0.84 | 0.03 |
| HP par=100 | 0.78 | 0.79 | 0.76 | -0.04 |
| HP par=6.25 | 0.81 | 0.81 | 0.81 | 0.01 |
| **corr(TFP, H)** | | | | |
| First Diff. | -0.10 | 0.00 | -0.21 | -0.21 |
| CF | -0.02 | 0.08 | -0.11 | -0.19 |
| HP par=100 | -0.14 | -0.03 | -0.27 | -0.24 |
| HP par=6.25 | -0.06 | 0.05 | -0.17 | -0.22 |
| **corr(LP, VA)** | | | | |
| First Diff. | 0.73 | 0.73 | 0.71 | -0.02 |
| CF | 0.72 | 0.71 | 0.74 | 0.02 |
| HP par=100 | 0.72 | 0.71 | 0.70 | -0.01 |
| HP par=6.25 | 0.72 | 0.71 | 0.71 | 0.00 |
| **corr(LP, H)** | | | | |
| First Diff. | -0.30 | -0.22 | -0.40 | -0.18 |
| CF | -0.23 | -0.13 | -0.32 | -0.19 |
| HP par=100 | -0.32 | -0.22 | -0.42 | -0.21 |
| HP par=6.25 | -0.27 | -0.16 | -0.38 | -0.21 |

Table 3: Average industry-level cyclical correlations between selected productivity measures and output, resp. hours. Weighted averages using constant industry weights over time: average nominal output share between 1960 and 1983. Comparison pre- and post-1984. Each correlation is computed using four different detrending methods.

aggregate correlations. On average, the correlation of measured industry productivity with industry output stayed virtually unchanged for both measures of productivity. Although there is on average a decrease in the correlations between industry productivity and industry hours, the difference between the two sub-periods is much smaller compared to the aggregate correlations. Moreover, table 4 shows that the average relative volatility of industry hours in comparison to industry output stayed virtually unchanged. This striking difference between the industry-level and aggregate correlations is the main motivation for conducting an analysis of the changes in cyclicality of productivity using the industry-level evidence.

Because the moments reported in tables 3 and 4 are crucial for the remainder of this paper, I briefly discuss their robustness. Complementary evidence is reported in Appendix B. Firstly, the stable industry-level correlations are not an artefact of the particular choice of weighting.

| **Standard deviation** | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| Value added ($VA$) | 7.82 | 8.02 | 7.62 | -0.40 |
| Hours ($H$) | 4.79 | 5.04 | 4.33 | -0.71 |
| std($H$)/ std($VA$) | 0.61 | 0.63 | 0.57 | -0.06 |
| std($TFP$)/ std($VA$) | 0.92 | 0.92 | 0.93 | 0.01 |

Table 4: Average volatility (in percent) and average relative volatility of selected industry-level variables, growth rates. Weighted averages using constant industry weights over time: average nominal output share between 1960 and 1983. Comparison pre- and post-1984.

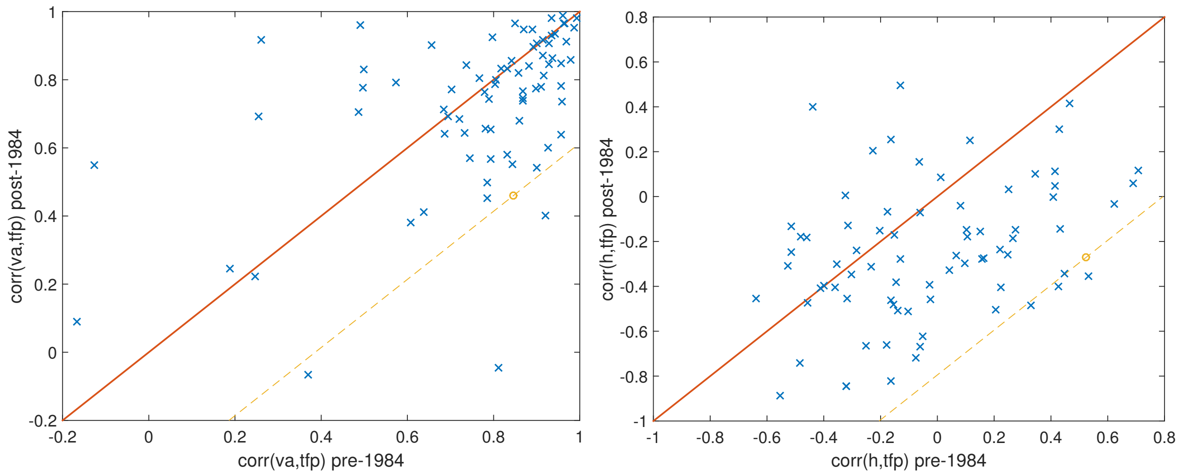


Figure 2: Correlations between measured industry TFP and value added (left) resp. hours (right). Comparison pre-1984 ($x$-axis) and post-1984 ($y$-axis). The red 45° line illustrates no change in correlations between the two sub-periods. The yellow dashed line illustrates the change in corresponding aggregate correlation.

The results are robust with respect to weighting by the nominal output shares in the second sub-period, or computing simple averages. Figure 2 depicts the individual industry-level correlations for periods pre- and post-1984 for the 77 industries. For many industries the correlations in the first and second sub-period differ substantially. However, there is no clear pattern showing a consistent decrease in correlations between output and measured productivity (left panel). The correlations between hours and productivity depicted in the right panel decreased for the majority of industries, however, the changes for most of the industries are relatively small. Only in four cases has the correlation between industry hours and productivity decreased in absolute value as much as the aggregate correlation, illustrated by the yellow dashed line. It is worth noting that the puzzling evidence in table 3 cannot be explained by the possibility that a small number of very big industries became more countercyclical in the second sub-period and in turn, affected the aggregate correlations. The industry averages reported in the table are already weighted by the industry size, thus taking this effect into account.

I use bootstrapping in order to compute the standard errors of the average correlations reported in table 3. The bootstrapped standard errors are small, see Appendix B for details.

### 2.3.1 Industry composition

Figure 2 reveals a substantial heterogeneity of correlations at the industry level. A possible explanation of how the aggregate correlations could have changed, even though the industry-level correlations on average stayed the same, is that the composition of industries might have changed. The procyclicality of aggregate productivity could decrease as a consequence of industries with countercyclical productivity growing bigger. I isolate the effect of composition by constructing counterfactual aggregate series in which I keep the industry composition constant over time. A comparison of the moments computed using the actual aggregate data versus the *fixed-composition* aggregate series shows that composition only played a minor role in decreasing the cyclicality of productivity.

| | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| **corr(TFP, VA)** | | | | |
| Aggregate series | 0.72 | 0.85 | 0.46 | -0.39 |
| Fixed composition | 0.70 | 0.83 | 0.51 | -0.32 |
| **corr(TFP, H)** | | | | |
| Aggregate series | 0.22 | 0.52 | -0.27 | -0.79 |
| Fixed composition | 0.22 | 0.53 | -0.19 | -0.72 |
| **corr(LP, VA)** | | | | |
| Aggregate series | 0.32 | 0.49 | 0.11 | -0.37 |
| Fixed composition | 0.43 | 0.60 | 0.27 | -0.33 |
| **corr(LP, H)** | | | | |
| Aggregate series | -0.29 | 0.04 | -0.63 | -0.66 |
| Fixed composition | -0.13 | 0.22 | -0.46 | -0.67 |

Table 5: Cyclical correlations between selected productivity measures and output, resp. hours. Comparison of aggregate series and counterfactual fixed-composition aggregate series, pre- and post-1984. Detrending method: growth rates.

According to the standard growth accounting, growth rate of any aggregate variable $X_t$ can be approximately expressed as

$$\tilde{X}_t \approx \sum_{i=1}^{N} w_{i,t} \tilde{x}_{i,t}, \tag{3}$$

where $\tilde{x}_{i,t}$ is the growth rate between periods $t$ and $t-1$ of industry-level variable $x_i$, and $w_{i,t}$ is an appropriately chosen time varying weight of industry $i$. The derivation of the approximation, weights, and a discussion on the quality of this approximation in the data set is provided in Appendix C.

I examine the counterfactual scenario in which the composition of the U.S. economy stays constant over time. I aggregate the industry level series using weights $\bar{w}_i$ that are fixed over time. I choose the weights to be the average shares of appropriately chosen nominal variables over the pre-1984 period, although the results are robust with respect to alternative choices of weighting. I plot the fixed-composition aggregate series and provide comparisons with the original aggregate series in Appendix C. If the composition effect is big, fixing the aggregation weights should substantially change the weighted average series, and consequently their second moments.

However, industry composition seems to have a limited effect on the change in cyclicality of aggregate productivity. Table 5 compares the correlations for aggregate growth rates from table 1 with the analogous correlations computed using fixed composition aggregate series. Composition has somewhat countercyclical effect in case of measured labor productivity, but this effect is present in both sub-periods. Importantly, as the last column of table 5 shows, the correlations between measured productivity and output resp. hours computed using the fixed-composition series decrease between the two sub-periods. The decrease is comparable with the actual aggregate series, reaching between 80% and 100% of the latter. The decrease in cyclicality of measured TFP for fixed composition series is quantitatively very similar to the results in table 1 in the case of growth rates and the Christiano-Fitzgerald band-pass filter, and somewhat smaller for the Hodrick-Prescott filtered series. The results for other detrending methods are reported in table 16 of Appendix C. I omit the calculation of standard errors as the point of the exercise is to isolate a component of observed changes in the actual realised data.

I conclude that a substantial part of the decrease in cyclicality of productivity is not explained by changes in composition of industries, although I can not rule out that the composition of industries had some effect on the observed changes. As I have already shown above that the industry-level correlations also did not change between the two periods, the limited effect of composition might be puzzling. In the next section, I shed more light on this issue by formally decomposing the change in cyclicality of aggregate productivity into the contribution of within-industry and cross-industry components.

### 2.3.2 Changing co-movement within industries and across industries

In what follows, I focus on the fixed-composition aggregate series described in the previous section. I work with the growth rates series, which are straightforward to decompose into a weighted sum of industry-level series. I defined the (growth rate of) fixed-composition aggregate variable $\bar{X}_t$ as

$$\bar{X}_t := \sum_{i=1}^{N} \bar{w}_i^X \tilde{x}_{i,t} \approx \tilde{X}_t, \tag{4}$$

where tilde denotes growth rates of variables and $\bar{w}_i^X$ are constant industry weights. For any pair of aggregate series $\bar{X}$, $\bar{Y}$ defined as in equation 4, the correlation coefficient can be decomposed into a within-industry and a cross-industry component as follows:

$$\begin{aligned} \text{Corr}\left(\bar{X}, \bar{Y}\right) &= \frac{\text{Cov}(\sum_{i=1}^{N} \bar{w}_i^X \tilde{x}_i, \sum_{i=1}^{N} \bar{w}_i^Y \tilde{y}_i)}{\text{std}\left(\bar{X}\right)\text{std}\left(\bar{Y}\right)} && (5) \\ &= \frac{\sum_{i=1}^{N} \bar{w}_i^X \bar{w}_i^Y \text{Cov}(\tilde{x}_i, \tilde{y}_i)}{\text{std}\left(\bar{X}\right)\text{std}\left(\bar{Y}\right)} + \frac{\sum_{i=1}^{N} \sum_{j\neq i}^{N} \bar{w}_i^X \bar{w}_j^Y \text{Cov}(\tilde{x}_i, \tilde{y}_j)}{\text{std}\left(\bar{X}\right)\text{std}\left(\bar{Y}\right)}. && (6) \end{aligned}$$

The first term of equation 6 collects the diagonal elements and reflects the co-movement between variables within individual industries. The second term collects all the off-diagonal elements and reflects the co-movement pattern across industries. The decomposition makes it clear that the aggregate correlation between variables might change as a consequence of changing co-movement patterns between industries, even when the within-industry co-movement stays the same.

Table 6 shows the result of the decomposition for the four aggregate correlations reported in table 5 for periods pre- and post-1984. The decomposition shows that the bulk of the decrease in cyclicality of productivity comes from the cross-industry component, reflecting the lower co-movement between industries. The within-industry component is in fact again an alternatively weighted average of the industry-level correlations. Its contribution to the change between the sub-periods is small, in line with the evidence in table 3. The change of the contribution of diagonal elements is very small for all four correlations, in two cases it is even positive. The cross-industry component, on the other hand, constitutes the vast majority of the change in aggregate correlations. The difference between the two components appears striking, but it

| | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| **corr(TFP, VA)** | | | | |
| Total correlation | 0.70 | 0.83 | 0.51 | -0.32 |
| Within-industry comp. | 0.22 | 0.19 | 0.29 | 0.10 |
| Cross-industry comp. | 0.48 | 0.64 | 0.21 | -0.43 |
| **corr(TFP, H)** | | | | |
| Total correlation | 0.22 | 0.53 | -0.19 | -0.72 |
| Within-industry comp. | -0.01 | -0.00 | -0.02 | -0.02 |
| Cross-industry comp. | 0.23 | 0.53 | -0.17 | -0.70 |
| **corr(LP, VA)** | | | | |
| Total correlation | 0.43 | 0.60 | 0.27 | -0.33 |
| Within-industry comp. | 0.22 | 0.22 | 0.24 | 0.02 |
| Cross-industry comp. | 0.21 | 0.38 | 0.03 | -0.35 |
| **corr(LP, H)** | | | | |
| Total correlation | -0.13 | 0.22 | -0.46 | -0.67 |
| Within-industry comp. | -0.05 | -0.05 | -0.05 | -0.00 |
| Cross-industry comp. | -0.09 | 0.26 | -0.41 | -0.67 |

Table 6: Decomposition of cyclical correlations between selected productivity measures and output, resp. hours into within-industry and cross-industry component. Comparison pre- and post-1984. Fixed-composition aggregate series constructed using average pre-1984 industry weights.

requires a careful interpretation.

While the decompositions are in terms of numbers in line with Wang (2014), we differ in terms of interpretation of the numbers. Wang computes the contribution of within- and cross-industry term to the correlation between measured TFP and input aggregate (consisting of appropriately weighted hours, capital, and intermediate inputs). She finds that the contribution of the within-industry component is 0.016 before 1984 and $-0.078$ after 1984. The change in the contribution of within-industry component is therefore $-0.094$, higher than in my decomposition. Nevertheless, it is smaller compared to $-0.52$, the contribution of the cross-industry component. The somewhat bigger (in absolute value) contribution of diagonal elements is partly attributable to a smaller number of industries used by Wang (2014).

Wang divides the contributions of diagonal and off-diagonal terms by the number of elements in each of the sums in equation 6, effectively scaling down the contribution of the off-diagonal component by the number of industries. She then interprets the result as within-industry changes being much more (five times more) important for the change of cyclicality of productivity than the cross-industry changes. However, I argue that this interpretation has several shortcomings:

- Normalizing the contribution of within- and cross-industry terms by the number of elements has no theoretical justification. In general, any change in co-movement of a single industry variable affects both the within-industry and cross-industry term. However, relative importance of these effects depends on the properties of data generating process, which are ex ante unknown. In my view, the best way to interpret the empirical results is to build an industry-level model and analyse its predictions for within-industry and cross-industry second moments.

- The conclusion provided in Wang (2014) is not robust. The result is very sensitive with respect to small changes in the contribution of the diagonal elements. My decomposition results show that the contribution of within-industry elements is positive, not negative, for two out of four correlations. This would completely reverse the conclusions of Wang (2014), even though the differences are small in absolute terms.

In the next section, I build a simple industry-level model which nests different mechanisms that are able to generate changes in the aggregate correlations. I compare the predictions of the model for aggregate and industry-level moments with the evidence summarized in this section. Most importantly, I assess the ability of the proposed mechanisms to generate the changes in aggregate correlations, while keeping the industry-level moments stable in line with tables 3 and 4.

# 3 Model

This section presents a simple multi-industry general equilibrium model that nests several explanations of the vanishing procyclicality of productivity that have been proposed in the literature. The procyclicality of measured productivity in the model decreases when the relative size of aggregate demand shocks decreases compared to the shocks to productivity (as in Barnichon 2010), or when the observed labor input (hours) becomes more flexible (as in Galí and van Rens 2019). The model is relatively close to Galí and van Rens (2019), the main innovation being that I model the economy at the level of industries. On the other hand, I keep the labor market simpler, in that I abstract from the explicit labor market friction.

The most essential features of the model are:

- production sector consisting of industries, products of which are imperfectly substitutable
- observable and unobservable labor supply margins, which create a wedge between measured and actual productivity
- demand- and supply-side shocks which affect either the aggregate economy as a whole, or have industry-specific effects

The economy is populated by a continuum of representative households and a continuum of firms belonging to one of $N$ symmetric industries. As there is no saving technology for the households and no capital, both the households and the firms solve a static problem in each period.

## 3.1 Firms

Each industry consists of a continuum of identical perfectly competitive firms represented by the unit interval. A firm belonging to industry $i$ produces output according to the production function

$$y_i = z_i l_i^{1-\alpha}, \tag{7}$$

where $z_i$ is industry-specific technology, $l_i$ is effective labor input of a firm in industry $i$, and $\alpha \in (0, 1)$ is a parameter that measures diminishing returns to labor. The effective labor input $l_i$ depends on hours worked $h_i$ and effort per hour $e_i$,

$$l_i = e_i h_i. \tag{8}$$

Effort in the model is the measure of workers' performance that can include any unobserved margins typically considered to be a part of labor utilization, e.g. unreported overtime hours or idle workers' time. Both hours and effort are provided by the households and are observable by the firm. The key difference between the two margins is that effort is typically not observable by the econometricians – standard measures of productivity therefore rely on the observable hours.

Industry specific technology $z_i$ consists of two exogenous stochastic components, the idiosyncratic industry technology $\bar{z}_i$ and aggregate technology $A$

$$z_i = A\bar{z}_i, \tag{9}$$

where both components are random variables following $\ln(\bar{z}_i) \sim \mathcal{N}(0, \sigma^z)$ and $\ln(A) \sim \mathcal{N}(0, \sigma^A)$.

The problem of a representative firm in industry $i$ is therefore to maximize profit

$$p_i z_i {l_i}^{1-\alpha} - w_i l_i, \tag{10}$$

taking as given the wage per unit of efficient labor input $w_i$ and the industry good price $p_i$. An optimizing firm chooses $l_i$ such that the marginal profit of increasing the effective labor input equals the marginal costs

$$(1-\alpha) p_i z_i {l_i}^{-\alpha} = w_i. \tag{11}$$

Firm profits $d_i$ are distributed to households in terms of lump sum payments,

$$d_i = \alpha p_i z_i {l_i}^{1-\alpha}. \tag{12}$$

### 3.2 Households

There is a continuum of identical households represented by the unit interval. Households provide labor input and consume goods. The objective of the representative household is to maximize its period utility

$$D \cdot u(C) - \sum_{i=1}^{N} g(e_i, h_i). \tag{13}$$

The consumption bundle $C$ is defined as

$$C = \left( \sum_{i=1}^{N} {v_i}^{\frac{1}{\sigma}} {c_i}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{14}$$

where $c_i$ is the consumption of industry $i$ good and $v_i$ is exogenous stochastic weight of industry $i$ in the consumption bundle. I interpret the weight $v_i$ as industry-specific demand shock.[8] Parameter $\sigma > 0$ is the elasticity of substitution between goods produced in various industries. The consumption bundle serves as the numeraire and all prices are expressed relative to its price.

Function $u(\cdot)$ measures the utility derived from consumption. It is continuous, concave and increasing in $C$. In all numerical exercises I assume CRRA preferences $u(C) = \frac{C^{1-\rho}}{1-\rho}$, where $\rho > 0$. Preference shock $D$ is an exogenous stochastic variable that is again drawn from a log-normal distribution. In line with Galí and van Rens (2019) I interpret it as a stand in for any non-technology aggregate disturbances.

Function $g(\cdot)$ measures the disutility of working. It is continuous, convex and increasing in both hours $h_i$ and effort $e_i$. The functional form used in this paper follows Barnichon (2010) and Bils and Cho (1994), and nests the special case in Galí and van Rens (2019):

$$g(e, h) = \lambda_h h^{1+\eta} + \lambda_e h e^{1+\epsilon}, \tag{15}$$

where $\lambda_h, \lambda_e, \eta, \epsilon > 0$. This form of $g(\cdot)$ implies that the disutility of effort per hour increases with hours worked. Parameters $\eta$ and $\epsilon$ determine the (inverse of) elasticity of hours and effort.

The households utility function (equation 13) is separable in labor supply across industries and includes the special case in which the utility of consumption is also separable, $\sigma = 1/\rho$. The separability assumption is not innocuous, but it allows me to keep the formulas simple and derive some intuitive insights analytically.

The representative household faces a budget constraint,

$$\sum_{i=1}^{N} w_i l_i + \sum_{i=1}^{N} d_i = \sum_{i=1}^{N} p_i c_i. \tag{16}$$

In equilibrium, both labor and goods market must clear in each industry, thus

$$c_i = y_i. \tag{17}$$

In the following sections I solve two sub-problems of optimal household behaviour: the optimal composition of consumption bundle and the optimal mixture of labor supply margins.

### 3.2.1 Optimal composition of consumption bundle

Recall that all prices are expressed relative to the price of consumption bundle. Given the price of industry $i$ good, the optimal demand for the industry $i$ good is given by a standard formula

$$c_i = v_i {p_i}^{-\sigma} C, \tag{18}$$

[8] Aggregate effect of industry-level demand shock is neutralised, $v_i = \bar{v}_i / \sum_{i=1}^{N} \bar{v}_i$, where $\ln \bar{v}_i \sim \mathcal{N}(0, \sigma^v)$.

and the definition of price index ensures that

$$C = \sum_{i=1}^{N} p_i c_i. \tag{19}$$

The elasticity of substitution $\sigma$ determines the reaction of the nominal output share of good $i$ to the change in its price. In the case of $\sigma$ being equal to one, the output share of each good is independent of its relative price. A positive shock to technology $z_i$ reduces the optimal price set by the competitive firms exactly by the size of the shock. Thus, the increase in the real demand of good $i$ caused by the reduced price is perfectly satisfied by the improvement in technology. For $\sigma$ equal to one, industry labor input does not respond to changes in industry technology.

### 3.2.2 Optimal composition of labor input

Given the firm demand for labor in each industry $\bar{l}_i$, household can provide any combination of hours and effort that satisfies $\bar{l}_i = e_i h_i$. Therefore, the representative household solves $N$ independent industry problems,

$$\min_{e_i, h_i} g(e_i, h_i) \tag{20}$$

$$\text{s.t.} \qquad \bar{l}_i = e_i h_i. \tag{21}$$

The first order conditions of the problem give

$$\frac{\partial g(e_i, h_i)/\partial e_i}{\partial g(e_i, h_i)/\partial h_i} = \frac{h_i}{e_i}. \tag{22}$$

As function $g$ is increasing in both $e_i$ and $h_i$, the term on the left hand side is positive and the households will always adjust both margins simultaneously in the same direction. Given the functional form 15, equation 22 implies

$$e_i = \left( \frac{\lambda_h}{\lambda_e} \frac{(1+\eta)}{\epsilon} \right)^{\frac{1}{1+\epsilon}} h_i^{\frac{\eta}{1+\epsilon}}. \tag{23}$$

The elasticity of effort with respect to hours thus depends on the term $\frac{\eta}{1+\epsilon}$, which I somewhat loosely refer to as the *elasticity ratio.*

### 3.2.3 Labor supply decision

Finally, the optimizing representative household chooses non-negative values for consumption $c_i$, effort $e_i$, and hours $h_i$ that maximize the utility function 13 given the budget constraint 16. Using the optimal firm behaviour condition 11, the budget constraint can be expressed as

$$\sum_{i=1}^{N} p_i z_i (e_i h_i)^{1-\alpha} = C. \tag{24}$$

Differentiating the Lagrangian associated with the household problem with respect to $c_i$ and $h_i$ and combining the associated first order conditions leads to the first order condition which determines the labor supply in the economy,

$$w_i e_i D C^{-\rho} = \frac{\partial g(e_i, h_i)}{\partial h_i} = \frac{\partial g(e_i, h_i)}{\partial e_i} \frac{e_i}{h_i}, \tag{25}$$

where the latter equation follows from 22. Similarly to many other RBC models, the response of hours to a technology shock can be both positive or negative and depends on the value of elasticity parameter $\rho$. In case of log-utility ($\rho = 1$), an increase in real wages following a technology shock is exactly offset by a decrease in marginal utility of consumption, thus the labor supply stays constant.

## 3.3 Equilibrium and model solution

The equilibrium in variables $C$, $h_i$, $e_i$, $w_i$, $p_i$, $y_i$ and $c_i$ is defined by the production function 7, firm optimality condition 11, household budget constraint 24, goods market clearing condition 17, optimal consumption choice 18, optimal composition of labor margins 23 and optimal labor input condition 25.

Despite its relative parsimony, the model can not be solved analytically. The main results of the paper follow from the numerical solution of the full non-linear version of the model presented in this section. I use the analytical solution of the linearised version of the model to build the basic intuition behind the results in sections 3.5 and 5.

## 3.4 Aggregation and measuring productivity

Aggregate output and hours are defined as simple sums of aggregate variables

$$Y = \sum_{i=1}^{N} y_i, \tag{26}$$

$$H = \sum_{i=1}^{N} h_i. \tag{27}$$

Because labor is the only production factor in the model, the single measure of productivity is output per hour

$$LP = Y/H, \tag{28}$$

$$lp_i = y_i/h_i. \tag{29}$$

I further refer to this measure as labor productivity or simply productivity. However, it is important to notice that this measure of productivity does not reflect any variation in capital services. Therefore, I consider measured total factor productivity to be the more suitable empirical counterpart, and use measured TFP instead of empirical measured labor productivity in the numerical execises.

### 3.5 Implications for cyclicality of productivity and flexibility of labor

In this section, I use the log-linearised version of the model in order to demonstrate that the cyclicality of measured aggregate productivity generated by my model depends both on the relative flexibility of hours and effort and on the relative importance of aggregate shocks to technology and demand. In what follows, I use the tilde symbol to denote the log-deviations of variables from their steady states.

Firstly, I illustrate how flexibility of hours and effort in my model influences the cyclicality of measured labor productivity, a mechanism similar to Galí and van Rens (2019). In log-deviations, production function 7 of industry $i$ can be expressed as

$$\tilde{y}_i = \tilde{z}_i + (1-\alpha)\tilde{e}_i + (1-\alpha)\tilde{h}_i, \tag{30}$$

$$\tilde{lp}_i = \tilde{y}_i - \tilde{h}_i = \tilde{z}_i + (1-\alpha)\tilde{e}_i - \alpha\tilde{h}_i. \tag{31}$$

After a positive non-technology shock, the increased demand can only be satisfied by increasing labor input. In the case when hours are relatively flexible and effort is very rigid, i.e. close to the standard case with only one labor input margin, labor productivity falls due to diminishing returns to labor. On the contrary, if hours are very rigid and effort is relatively flexible, measured labor productivity increases with labor input due to the procyclical role of factor utilization. Expressing the optimal effort from the optimality condition 23 and plugging it into equations 30 and 31 gives

$$\tilde{y}_i = \tilde{z}_i + B\tilde{h}_i, \tag{32}$$

$$\tilde{lp}_i = \tilde{z}_i + \Gamma\tilde{h}_i, \tag{33}$$

where constants $B$ and $\Gamma$ are defined as

$$B = (1-\alpha)\left(1 + \frac{\eta}{1+\epsilon}\right), \tag{34}$$

$$\Gamma = -\alpha + (1-\alpha)\frac{\eta}{1+\epsilon}. \tag{35}$$

The response of output and productivity to an increase in hours depends on the degree of diminishing returns to labor $\alpha$, and on the *elasticity ratio* $\frac{\eta}{1+\epsilon}$. Importantly, parameter $\Gamma$ determines the response of productivity and can have both positive or negative values.

Let us first consider the implications of the extreme values of parameters $\eta$ and $\epsilon$. If $\epsilon$ is very high compared to $\eta$, effort is very rigid and $\frac{\eta}{1+\epsilon}$ goes to zero. In that case, the response of measured labor productivity to a change in hours is driven by the diminishing returns and $\Gamma$ is negative. This might be the case if effort is very rigid ($\epsilon \to \infty$), or if hours are very elastic ($\eta \to 0$).

On the other hand, if $\eta$ is very high in comparison to $\epsilon$, adjusting hours is very costly in terms of utility. The optimizing households and firms choose to rely less on adjusting hours and more on adjusting effort. As a result, the observable labor input fluctuates less, but its correlation with measured labor productivity is positive. In fact, the coefficient $\Gamma$ becomes positive for any $\frac{\eta}{1+\epsilon} > \frac{1}{2}$ in the case of the standard value of diminishing returns parameter $\alpha = 1/3$. To sum up, an increase in the relative flexibility of hours leads to a decrease in correlation between hours and measured productivity accompanied by an increase in relative volatility of hours.

Secondly, I discuss the role of the shock composition. Naturally, labor productivity in equation 33 positively depends on exogenous technology $z_i$. However, the reaction of hours to an improvement in technology can be both positive or negative, depending on the parameter values. Empirical estimates of the response of hours to technology improvements typically show that it is relatively small in absolute value and negative, both at the aggregate and industry level; see e.g. Galí (1999) and Holly and Petrella (2012).

Taking into account the empirical literature, the standard values of consumption elasticity $\rho$ close to the log-utility case and the elasticity of substitution between goods of various industries $\sigma$ close to one appear plausible. For $\sigma$ close to one, the model generates small conditional volatility of industry hours and small (and possibly negative) covariance between industry hours and productivity. The same is true for the corresponding aggregate moments in the case when $\rho$ is close to one. On the other hand, the previous paragraphs show that for a sufficiently high elasticity ratio $\frac{\eta}{1+\epsilon}$, the non-technology shocks in the model generate positive co-movement between hours and productivity. Therefore, a shift in the composition of shocks from demand to more important technology shocks may decrease the unconditional correlation.

Log-linearising the equations for aggregate output, hours, and labor productivity, it is straightforward to derive that

$$\tilde{LP} = \tilde{Y} - \tilde{H} \approxeq \tilde{Z} + \Gamma \tilde{H}, \tag{36}$$

where $\tilde{Z} = \frac{1}{N}\sum_{i=1}^{N} \tilde{z}_i$ is the average growth rate of the industry technology. Notice that equation 36 is analogous to industry-level equation 33. Thus, the relationship between aggregate labor productivity and hours depends on the parameters in a way that is similar to the industry-level variables.

### 3.6 Discussion

It is straightforward to relate my model to Galí and van Rens (2019), although there are several differences. Galí and van Rens interpret the measure of observable labor input in their model as employment, assuming fixed hours per worker. They also use a special case of the utility function featured in my model, with only one industry and linear disutility of working, the case analogous to $\eta = 0$. Thus, without any other frictions at work, households in Galí and van Rens would optimally choose constant effort and would always satisfy the changes in demand for labor by varying employment. Nevertheless, Galí and van Rens introduce quadratic hiring costs which ensure that workers' effort indeed varies over time. Their main exercise is to study the effect of the reduction of hiring costs on the cyclicality of labor productivity.

In order to keep the problem simple at the industry and aggregate level, I abstract from the hiring frictions and study the effect of varying the value of elasticity $\eta$. Both approaches generate changes in cyclicality of productivity through changing how flexibly observed labor input responds. In an alternative formulation of my model which also features quadratic costs of adjusting hours in a simple form, the close relationship between the two approaches is confirmed. The results are equivalent to the version presented in this paper, but the number of parameters that need to be identified increases and the formulas become more complicated and less intuitive.

# 4 Quantitative analysis

## 4.1 Model calibration

I simulate the model at quarterly frequency and calibrate the parameters accordingly. I subsequently convert the simulated series into annual frequency in order to obtain series which are comparable with the industry-level data set. The benchmark calibration targets selected second moments of the pre-1984 sample. I prefer to use the data moments computed using the growth rates of fixed-weight aggregate variables, as these are the most directly comparable with the model. The choice of aggregate series does not influence the main results. The benchmark calibration is summarized in table 7.

The model economy consists of $N = 77$ industries. Some of the model parameters are set to values that are standard in the macroeconomic literature. I set the curvature of production function $\alpha$ to 1/3 and assume log-utility of consumption $\rho = 1$.[9] The elasticity of substitution between industry goods $\sigma$ is chosen quite arbitrarily at 0.9. Robustness checks show that the value of elasticity $\sigma$ does not substantially influence the results. The elasticity of substitution affects the strength of the response of industry-level variables to industry-specific shocks. Thus, the main impact of choosing alternative values of $\sigma$ is that it alters the size of industry-specific shocks in the model necessary to generate the fluctuations of industry variables with a realistic magnitude.

Utility function parameters $\lambda_h$ and $\lambda_e$ are scaling the model variables in a way that does not influence the results. I normalize $\lambda_e$ such that there is unit effort in the steady state and choose $\lambda_h$ to scale the size of steady state aggregate output. I calibrate the benchmark inverse elasticity of hours $\eta$ to be at the lower end, but yet consistent with the values used in the macroeconomic literature. Macroeconomists typically focus on the elasticity of observed labor input with respect to wages, referred to as Frisch elasticity. In my model, Frisch elasticity depends on both parameters governing the flexibility of hours and effort and equals $\frac{1}{\eta}\left(1 + \frac{1}{\epsilon}\right)$. In line with the values used in modern DSGE models, I calibrate the Frisch elasticity to 0.5; see e.g. de Walque et al. (2015). For any given effort elasticity parameter $\epsilon$, the Frisch elasticity pins down the value of hours elasticity parameter $\eta$.

The remaining preference parameter $\epsilon$ governs the elasticity of effort, thus pinning down the strength of the factor utilization channel in my model. Effort is typically not directly observed and I have little guidance from the literature concerning the value of the parameter. I calibrate $\epsilon$ jointly with the relative variance of aggregate demand shock $\sigma_D^2$ targeting two second moments from the pre-1984 sample: the relative volatility of hours with respect to output and the correlation of aggregate hours with measured TFP. The analysis in section 3.5 shows that the two parameters are well identified by the targets, as they have contrasting effects on the target values. A higher share of demand shocks increases both relative volatility of hours and, for elasticity ratio $\frac{\eta}{1+\epsilon}$ above a certain threshold, also the correlation of aggregate hours with

[9] I report the robustness exercises with respect to $\rho$, $\sigma$ and Frisch elasticity of labor supply in Appendix D.

| **Parameter** | Symbol | Value | Source or target |
|---|---|---|---|
| Number of industries | $N$ | 77 | data set, Jorgenson (2008) |
| Returns to labor | $\alpha$ | 1/3 | standard |
| Consumption elasticity | $\rho$ | 1 | standard (robustness analysis) |
| Elasticity of substitution | $\sigma$ | 0.9 | standard (robustness analysis) |
| Utility weight, hours | $\lambda_h$ | $3.7 \times 10^{-4}$ | normalisation $Y^{ss} = 100$ |
| Utility weight, effort | $\lambda_e$ | $1.5 \times 10^{-3}$ | normalisation $e^{ss} = 1$ |
| **Hours elasticity** | $\eta$ | 2.68 | Frisch elasticity 0.5 (robustness) |
| Effort elasticity | $\epsilon$ | 2.96 | pre-1984 corr$(TFP, H)$ |
| Variance agg. technology | $\sigma_A^2$ | | pre-1984 Var$(VA)$ |
| **Variance agg. demand** | $\sigma_D^2$ | | pre-1984 ratio std$(H)/$ std$(VA)$ |
| Variance ind. technology | $\sigma_z^2$ | | pre-1984 mean std$(tfp_i)/$ std$(TFP)$ |
| Variance ind. demand | $\sigma_v^2$ | | pre-1984 mean std$(va_i)/$ std$(VA)$ |

Table 7: Benchmark calibration of the model parameters. The main exercise of this section is to vary the values of key parameters, depicted in bold font.

productivity. A higher value of $\epsilon$ also increases the volatility of hours, as the agents rely more on adjusting hours and less on adjusting effort. However, a higher value of $\epsilon$ at the same time brings the correlation between aggregate hours and productivity down, due to a smaller contribution of pro-cyclical effort. Thus, conditional on other parameter values, there exists a unique pair of $\epsilon$ and $\sigma_D$ matching both targets. The calibrated value of $\epsilon$ roughly equals 3 is in line with the values used in Galí and van Rens (2019) and Barnichon (2010).

Concerning the remaining shocks in the model, I calibrate their volatilities to roughly match the standard deviations of variables in the pre-1984 sample period. The volatility of aggregate technology shock $\sigma_A$ is calibrated to match the volatility of aggregate output. The relative volatilities of industry specific shocks are set to match the standard deviation of industry-level fluctuations compared to the aggregate fluctuations in the pre-1984 period. Average (across industries) standard deviation of industry productivity relative to the aggregate productivity pins down $\sigma_z$. Average standard deviation of industry output relative to the aggregate output pins down $\sigma_v$. The shocks are not autocorrelated, although adding autocorrelation does not affect the results.

Table 8 shows the approximate variance decomposition of selected aggregate and industry-level variables simulated by the model. The benchmark calibration implies that the preference shock generates roughly 97% of the variance of the aggregate output and 29% of the variance of the aggregate productivity. The decompostion also shows that the aggregate shocks are relatively unimportant for the dynamics of the industry-level variables. Both aggregate shocks together explain about 12% of the variance of industry hours and output, and about 3% of the variance of industry productivity. Industry variables are mostly driven by the shocks affecting their own industry-specific conditions.

The main exercise for which I use the calibrated model is to vary the key parameter values in order to test the effects on the aggregate and industry-level moments. I vary the values of the following:

- Parameter $\eta$, which pins down the flexibility of hours. I change $\eta$ from 2.7 to 1.8, such that the correlation of aggregate productivity with hours changes from the pre-1984 value (0.53)

| **Variance decomposition** | Aggregate shocks | | Industry shocks | |
|---|---|---|---|---|
| | technology | demand | technology | demand |
| **Aggregate variables** | | | | |
| Output | 0.02 | 0.97 | 0.01 | 0.00 |
| Productivity | 0.43 | 0.29 | 0.28 | 0.00 |
| Hours | 0.00 | 1.00 | 0.00 | 0.00 |
| **Industry variables** | | | | |
| Output | 0.00 | 0.11 | 0.10 | 0.79 |
| Productivity | 0.02 | 0.01 | 0.89 | 0.08 |
| Hours | 0.00 | 0.13 | 0.00 | 0.87 |

Table 8: Variance decomposition of the selected model variables. Approximate share of variance explained by each type of shock. For industry variables, the decomposition of the average variance is reported. Benchmark calibration.

to the post-1984 value (-0.19). This corresponds to an increase in volatility of aggregate hours by roughly 30%. The experiment demonstrates the effect of increased flexibility of labor input in the period after 1984, and is roughly in line with the main exercise in Galí and van Rens (2019).

- Volatility of aggregate shock $\sigma_D$, such that the standard deviation of output changes from the pre-1984 value (0.028) to the post-1984 value (0.018). This corresponds to a change from aggregate demand shock explaining about 97% of the variance of output to explaining about 92%. The volatility $\sigma_D$ decreases by around 42%, in line with the decrease identified in the literature; see e.g. Barnichon (2010).

## 4.2 Results

I solve the full non-linear model numerically and simulate the model economy for ten thousand periods in each of the exercises described below. I compute the second moments from the simulated series using the same detrending procedure as for their data counterparts.

The simulation results together with their data counterparts are summarized in tables 9 and 10. Top panel of table 9 displays again the key aggregate moments from the data for periods pre- and post-1984. The bottom panel of table 9 shows the corresponding aggregate moments generated by the model. The benchmark calibration matches the pre-1984 data moments very well, as three out of four moments are actually targeted in the calibration. The bottom panel of table 9 also reports the results for the two alternative parameter values: a lower value of $\eta$ corresponding to a higher flexibility of hours, and a lower volatility of aggregate demand shock $\sigma_D$.

### 4.2.1 Change in flexibility of labor input

In the first exercise, I decrease $\eta$ to two thirds of its benchmark value, such that the correlation of hours with productivity matches its post-1984 value of $-0.19$. This alternative calibration generates volatility of hours 30% higher and factor utilization volatility 13% smaller compared to the benchmark case. As expected, decreasing $\eta$ leads to a simultaneous decrease in procyclicality of aggregate productivity and an increase in relative volatility of hours, in line

| **Aggregate** | correlation productivity with output | with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.83 | 0.53 | 0.89 | 0.028 |
| Post-1984 | 0.51 | -0.19 | 1.20 | 0.018 |
| **Model** | | | | |
| Benchmark calibration | 0.67 | 0.53 | 0.89 | 0.028 |
| Flexible hours, $\eta = 1.8$ | -0.05 | -0.19 | 1.02 | 0.032 |
| Smaller dem. shocks | 0.59 | 0.34 | 0.85 | 0.018 |

Table 9: Selected aggregate second moments. Data (top panel) and model simulations (bottom panel).

with the explanation proposed by Galí and van Rens (2019). The drop in the correlation of productivity with output overshoots its data counterpart, while the relative standard deviation of hours increases less in comparison to the data. Qualitatively, the model successfully replicates the post-1984 change in the aggregate moments.

However, table 10 reveals that the higher flexibility of hours generates counter-factual changes in the average industry-level moments. The model simulation results show that:

- average volatility of industry hours relative to industry output in the model increases compared to the benchmark case as much as for the aggregate hours. In the data, the industry-level relative standard deviation actually mildly decreased between the two time periods.
- average correlation of productivity with output in the model decreases substantially compared to the benchmark case. Although the decrease in correlation of industry variables generated by the model is somewhat smaller than for the aggregate variables, it is comparable in magnitude. In the data, the average industry-level correlation stayed virtually unchanged between the two sub-samples.
- average correlation of industry-level productivity with industry hours in the model decreases substantially. Although the decrease in correlation of industry variables generated by the model is somewhat smaller than for the aggregate variables, it is still twice as big as the change between the two sub-samples in the data.
- standard deviation of output at both industry and aggregate level in the model increases, as labor becomes more flexible. In the data, the period of Great Moderation is characterised by a decrease in volatility of output.

The apparent problem with the change in flexibility of hours $\eta$ is that it generates changes in second moments that are too similar at the aggregate and industry level. In section 5 I provide a detailed discussion of why this is the case.

### 4.2.2 Change in composition of aggregate shocks

Table 9 and table 10 also display the simulated moments for another alternative parameter value, a lower volatility of the aggregate demand shock. Several authors, for example Barnichon

| Industry | correlation productivity with output | with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.81 | 0.00 | 0.63 | 0.080 |
| Post-1984 | 0.79 | -0.21 | 0.57 | 0.076 |
| **Model** | | | | |
| Benchmark calibration | 0.59 | 0.30 | 0.85 | 0.083 |
| Flexible hours, $\eta = 1.8$ | 0.18 | -0.11 | 0.99 | 0.093 |
| Smaller dem. shocks | 0.59 | 0.28 | 0.84 | 0.079 |

Table 10: Selected averages of industry-level second moments. Data (top panel) and model simulations (bottom panel).

(2010) and Galí and Gambetti (2009), have suggested that the Great Moderation period after 1984 was characterised by a different composition of shocks, especially smaller demand side shocks, or muted effects of these shocks on the economy.

Recall that the benchmark calibration uses consumption elasticity $\rho$ equals one, which implies that hours do not respond to the technology shocks. Thus, both technology and non-technology shocks generate a non-negative conditional correlation between hours and productivity. Consequently, as I further discuss in section 5, a change in the composition of shocks can decrease the correlation between productivity and hours, but can not reverse the sign of the correlation. Moreover, given the benchmark value of the elasticity ratio $\frac{\eta}{1+\epsilon}$, there is a positive lower bound on the correlation between productivity and output. For that reason, I can not use the negative aggregate correlation between productivity and hours in the post-1984 sample as the calibration target for this exercise. Instead, I choose to change the volatility of aggregate demand shock $\sigma_D$ such that the model roughly matches the volatility of aggregate output in the post-1984 period. Such a decrease of $\sigma_D$ is also consistent with the exercise conducted by Barnichon (2010).

The alternative calibration changes the relative importance of the different types of shocks. The preference shock generates roughly 92% of the variance of aggregate output and 13% of the variance of aggregate productivity. The aggregate productivity is mostly explained by the aggregate technology shock (52% of variance) and the industry technology shocks (35%).

The last row of table 9 shows that the decrease in $\sigma_D$ indeed drives the cyclicality of measured aggregate productivity down. Although the changes in aggregate correlations are smaller compared to the data, I argue that the results are sufficient in demonstrating the key insight of the paper. The changes in the composition of aggregate shocks may decrease the aggregate correlations, while keeping the industry-level moments virtually unchanged. The two types of shocks within my model are clearly too simple to reflect the whole extent of the structural changes happening during the Great Moderation period. However, the point of the exercise is to show that the composition of aggregate shocks has qualitatively very different effects on the aggregate and industry-level moments. The industry-level model simulation results with the alternative value of $\sigma_D$ are reported in the last row of table 10. The simulation results show that:

- average correlation of industry productivity with industry output in the model stays virtually unchanged, in line with the empirical evidence.

- average correlation of industry productivity with industry hours in the model stays unchanged, while in the data it slightly decreases.

- volatility of industry hours relative to industry output in the model stays virtually unchanged, in line with the empirical evidence.

  Notice that the model also predicts a small decrease in the relative volatility of aggregate hours. Changing the composition of shocks in my model does not explain the increase in the relative volatility. My results also in no way rule out the possibility that the increase in the relative volatility of aggregate hours was driven by the higher flexibility in the labor markets in the post-1984 period. I leave the question open for the ongoing research in the Great Moderation literature.

- standard deviation of output in the model decreases, as aggregate shocks in total become smaller, in line with the Great Moderation episode.

To summarize the main findings, both exercises (increasing the flexibility of hours and lowering the relative size of aggregate demand shocks) are able to qualitatively replicate the decrease in the procyclicality of aggregate productivity within my model framework. However, the change in the relative size of shocks appears to be more successful in simultaneously replicating the second moments at the industry level. The next section explains the intuition behind the results based on the analytical formulas derived for the industry and aggregate second moments.

## 5 Analytical insights

In this section, I use the log-linearised model equations in order to build the intuition behind the main results presented in section 4.2. I discuss the impact of the relative flexibility of hours and effort and the impact of the relative importance of aggregate shocks to technology and demand on the second moments of interest. I explain why the two mechanisms differ in their implications for the industry-level moments. I follow the same notation as in the previous sections and use the tilde symbol to denote the log-deviations of variables from their steady states.

Recall that equations 32 and 33 state that

$$\tilde{y}_i = \tilde{z}_i + B\tilde{h}_i,$$

$$\tilde{lp}_i = \tilde{z}_i + \Gamma\tilde{h}_i,$$

where constants $B$ and $\Gamma$ are defined as

$$B = (1-\alpha)\left(1 + \frac{\eta}{1+\epsilon}\right),$$

$$\Gamma = -\alpha + (1-\alpha)\frac{\eta}{1+\epsilon}.$$

Coefficients $B$ and $\Gamma$ determine the response of output and productivity, respectively, to an increase in hours. Moreover, for the aggregate variables it holds that

$$\tilde{Y} \approxeq \tilde{Z} + B\tilde{H},$$

$$\tilde{LP} \approxeq \tilde{Z} + \Gamma\tilde{H},$$

where $\tilde{Z} = \frac{1}{N}\sum_{i=1}^{N} \tilde{z}_i$ is the average growth rate of the industry technology.

Using these equations it is straightforward to derive the approximate expressions for the key aggregate and industry-level variances and correlations in the model. In the next section, I use these expressions in order to build the intuition behind the key model properties reported in section 4.2.

## 5.1 Relative volatility of hours

**Property 1** *Within the model environment, both a change in the relative flexibility of hours and effort and a change in the relative composition of aggregate shocks can generate a variation in the relative volatility of aggregate hours. However, an increase in the relative flexibility of hours also necessarily increases the relative volatility of hours at the level of individual industries, while a change in the composition of aggregate shocks does not.*

The relative variance of industry hours and output in my model after detrending can be expressed as

$$\frac{\operatorname{Var}(\tilde{h}_i)}{\operatorname{Var}(\tilde{y}_i)} = \frac{\operatorname{Var}(\tilde{h}_i)}{\operatorname{Var}(\tilde{z}_i) + B^2 \operatorname{Var}(\tilde{h}_i) + 2B \operatorname{Cov}(\tilde{z}_i, \tilde{h}_i)}. \tag{37}$$

Recall that in the case when the elasticity of substitution $\sigma$ equals one, labor input does not respond to changes in industry technology and the covariance between $\tilde{z}_i$ and $\tilde{h}_i$ is zero. In that case, we can rewrite the previous equation as

$$\frac{\operatorname{Var}(\tilde{h}_i)}{\operatorname{Var}(\tilde{y}_i)} = \frac{1}{\frac{\operatorname{Var}(\tilde{z}_i)}{\operatorname{Var}(\tilde{h}_i)} + B^2}. \tag{38}$$

Equation 38 expresses the relative volatility of hours in terms of two factors: the parameter $B$, and the relative variance of industry technology $\tilde{z}_i$ and hours $\tilde{h}_i$.[10]

I first discuss the role of the relative size of aggregate shocks. In equation 38, exogenous shocks only influence term $\frac{\operatorname{Var}(\tilde{z}_i)}{\operatorname{Var}(\tilde{h}_i)}$. While the numerator $\operatorname{Var}(\tilde{z}_i)$ only reflects the shocks to technology, the denominator only reflects the shocks to demand in the case when $\sigma$ is one. An increase in the relative variance of technology shocks $\tilde{z}_i$ decreases the relative variance of industry hours and output.

Recall that equation 9 states that the industry technology depends on an aggregate and an idiosyncratic industry-specific component, $\tilde{z}_i = \tilde{A} + \tilde{\tilde{z}}_i$. Industry demand also depends on an aggregate component (preference shock $D$) and an idiosyncratic component (stochastic weight $v_i$). The key piece of intuition is the property that the aggregate shocks explain a minor part

[10]The robustness exercise in Appendix D shows that the non-zero covariance term arising from choosing the value of $\sigma \neq 1$ does not substantially alter the result.

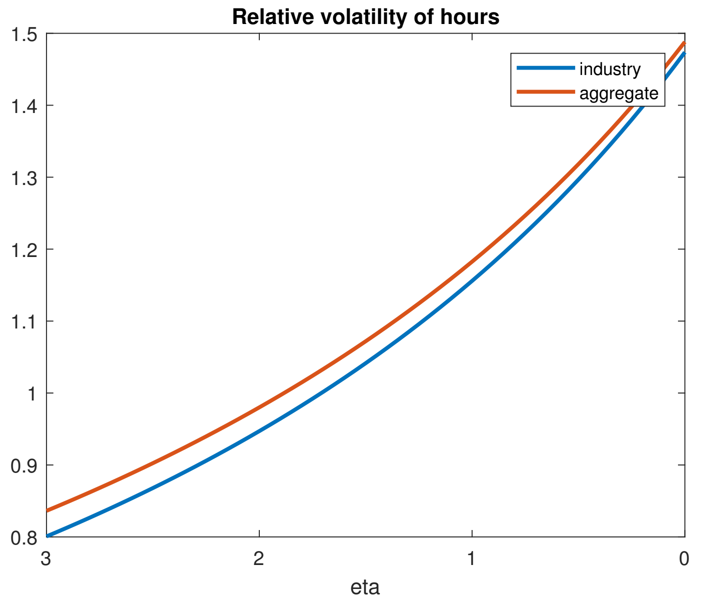


Figure 3: Comparison between the aggregate and industry relative volatility of hours (y-axis) for varying elasticity of hours $\eta$ (x-axis). Benchmark calibration.

of the fluctuations of industry-level variables, while the idiosyncratic component explains the major part, see section 4.1. In other words, industry-level variables are mostly driven by shocks specific to the own industry. This property is a typical result in the literature on industry business cycles; see e.g. Horvath (2000), Acemoglu et al. (2012). Because aggregate technology and demand shocks explain a very small fraction of the variance of industry variables $\tilde{z}_i$ and $\tilde{h}_i$, a change in their relative importance has a very limited effect on the term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$, and does not change the relative volatility of industry hours significantly.

On the other hand, a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences both terms in the denominator on the right hand side of equation 38. In the case of very rigid hours, when $\frac{\eta}{1+\epsilon}$ goes to infinity, both terms in the denominator go to infinity. Thus, the relative variance of hours goes to zero. In contrast to a change in the relative size of aggregate shocks, a change in the relative flexibility of hours and effort generates a substantial change in the relative volatility of industry hours.

The relative variance of aggregate hours and output can be derived analogously to equation 38. Recall that in the case when CRRA utility parameter $\rho$ equals one, the covariance between technology $\tilde{Z}$ and hours $\tilde{H}$ is again zero. In that case we get

$$\frac{\mathrm{Var}(\tilde{H})}{\mathrm{Var}(\tilde{Y})} \approx \frac{1}{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + B^2}, \tag{39}$$

where the approximation sign reflects the approximate relation in equation 36.[11] A comparison of equations 38 and 39 delivers the two main insights of the exercise.

Firstly, in contrast to the industry level, a change in the relative size of aggregate shocks may change the relative volatility of aggregate hours. The key difference in comparison to

[11]The robustness exercise in Appendix D shows that the non-zero covariance term arising from choosing the value of $\rho \neq 1$ does not substantially alter the result.

the industry volatility is that the aggregate shocks explain a large part of the fluctuations of aggregate macroeconomic variables. The idiosyncratic industry shocks on average cancel out to a large extent and are less important in the aggregate. Thus, the relative variance of average technology level $\tilde{Z}$ and aggregate hours $\tilde{H}$ is more strongly affected by changes in the relative importance of aggregate technology and demand shocks.

Secondly, the similarity between equations 38 and 39 reveals that a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences the relative variance of hours at the aggregate and industry level in an analogous way. The only difference between the two expressions is the relative variance term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$, resp. $\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})}$, but the contribution of these terms occurs to be relatively small. Figure 3 plots the comparison between the aggregate and industry-level relative volatility of hours for the benchmark model calibration, varying the value of utility parameter $\eta$ which pins down the flexibility of hours. The figure illustrates that changes in $\eta$ generate changes in the relative volatility of hours at the aggregate and industry level that are quite similar in magnitude.

## 5.2 Correlation between productivity and hours

**Property 2** *Within the model environment, both a change in the relative flexibility of hours and effort and a change in the relative composition of aggregate shocks can generate changes in the aggregate correlations qualitatively in line with the empirical evidence. However, an increase in the relative flexibility of hours also necessarily decreases the correlations between productivity and hours (resp. output) at the level of individual industries, while a change in the composition of aggregate shocks does not.*

In this section I focus on deriving the properties of the correlation between measured productivity and hours, using equation 33. Appendix E.1 shows the derivations for the correlation between measured productivity and output and discusses the analogous properties.

At the industry level, the correlation between measured productivity and hours can be expressed as

$$\mathrm{Corr}(\tilde{lp}_i, \tilde{h}_i) = \frac{\frac{\mathrm{Cov}(\tilde{z}_i,\tilde{h}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma}{\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma^2 + 2\Gamma\frac{\mathrm{Cov}(\tilde{z}_i,\tilde{h}_i)}{\mathrm{Var}(\tilde{h}_i)}}}. \tag{40}$$

In the case when the elasticity of substitution $\sigma$ equals one, the covariance between industry technology and hours is zero. In that case, I obtain

$$\mathrm{Corr}(\tilde{lp}_i, \tilde{h}_i) = \frac{\Gamma}{\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma^2}}. \tag{41}$$

Equation 41 expresses the correlation in terms of two factors: the parameter $\Gamma$, and the relative variance of industry technology $\tilde{z}_i$ and hours $\tilde{h}_i$.

Again, I first discuss the role of the relative size of aggregate shocks. In equation 41, the exogenous shocks only influence term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$. An increase in the relative size of technology shock $z_i$ decreases the absolute value of the correlation, but does not reverse its sign. As discussed in detail above, a change in the relative size of the aggregate technology and demand shocks

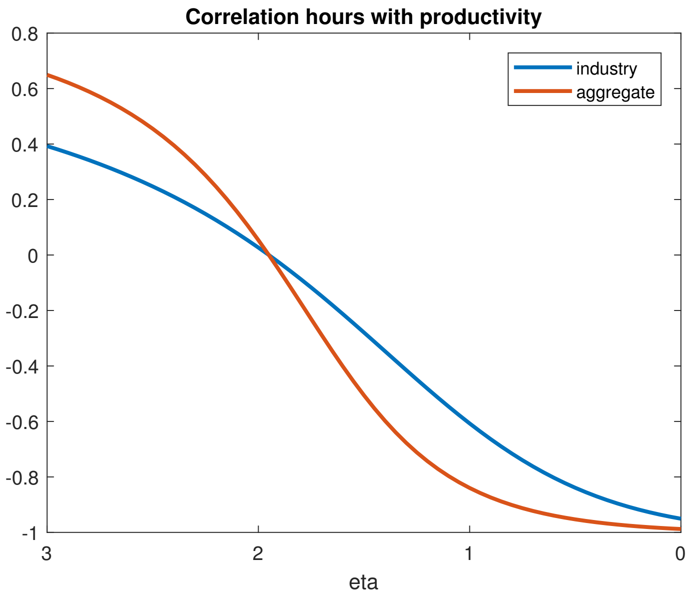


Figure 4: Comparison between the aggregate and industry correlation between labor productivity and hours (y-axis) for varying elasticity of hours $\eta$ (x-axis). Benchmark calibration.

can not generate a big change in the term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$. The reason is that the aggregate shocks only explain a small part of the variance of industry-level variables.

On the other hand, a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences all terms on the right hand side of equation 41. Coefficient $\Gamma$ defined in equation 35 determines the sign of the correlation. In the case of very flexible hours, the elasticity ratio goes to zero and $\Gamma$ is negative. In the case when hours are extremely rigid, the elasticity ratio goes to infinity and the correlation approaches one.

The correlation between aggregate productivity and hours can be derived analogously to equation 41. In the case when the utility parameter $\rho$ is equal to one, the covariance between technology $\tilde{Z}$ and hours $\tilde{H}$ is zero and I get

$$\mathrm{Corr}(\tilde{LP}, \tilde{H}) = \frac{\Gamma}{\sqrt{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + \Gamma^2}}. \tag{42}$$

The comparison of equations 41 and 42 delivers another two insights which are key for the results of this paper.

Firstly, a change in the relative size of aggregate technology and demand shocks can generate a change in the correlation between productivity and hours at the aggregate level, but not at the industry level. The key difference between the aggregate and the industry level is again that the aggregate shocks explain a substantial part of the variance of the aggregate variables, but only a minor part of the industry variables. Thus, the relative variance of average technology level $\tilde{Z}$ and aggregate hours $\tilde{H}$ is strongly affected by the relative importance of aggregate technology and demand shocks, while the relative variance of industry technology $\tilde{z}_i$ and industry hours $\tilde{h}_i$ is not.

Secondly, a change in the elasticity ratio $\frac{\eta}{1+\epsilon}$ influences the correlation at the aggregate and industry level in an analogous way. The only difference between the two expressions is the

| | Benchmark calibration | Higher flexibility of hours | Lower variance demand shock |
|---|---|---|---|
| **corr( $*$ , VA)** | | | |
| Technology $Z$ | 0.17 | 0.15 | 0.33 |
| Utilization-adjusted productivity | -0.76 | -0.84 | -0.36 |
| Utilization component | 0.99 | 0.99 | 0.95 |
| **corr( $*$ , H)** | | | |
| Technology $Z$ | 0 | 0 | 0 |
| Utilization-adjusted productivity | -0.86 | -0.91 | -0.65 |
| Utilization component | 1 | 1 | 1 |
| **Relative volatility** | | | |
| std(Utilization)/std(Adj. prod.) | 1.2 | 0.8 | 0.6 |
| std(Utilization)/std(Technology) | 2.3 | 2.0 | 1.2 |

Table 11: Decomposition of the measured productivity into factor utilization component and utilization-adjusted productivity. Simulated series with benchmark calibration and two alternative calibrations: higher flexibility of hours and lower variance of demand shock.

relative variance term $\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)}$, resp. $\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})}$, but the contribution of this term seems to be rather small. Figure 4 plots the comparison between aggregate and industry-level correlations for the benchmark calibration, varying the value of parameter $\eta$ that pins down the flexibility of hours. The figure shows that changes in parameter $\eta$ generate changes in the correlation between productivity and hours at the aggregate and industry level that are similar in magnitude.

To summarize the key intuition provided in this section, an increase in the relative flexibility of observable labor supply margin within my model leads to a decrease in procyclicality of measured aggregate productivity in line with the literature. However, it also generates a decrease (of a comparable magnitude) in the industry-level correlations, which is not in line with the empirical evidence. On the contrary, a change in the relative variance of technology and non-technology aggregate shocks generates a change in the aggregate correlations while the industry-level correlations stay unaffected.

# 6 Role of factor utilization

Fernald and Wang (2016) make a handful of important observations about the nature of change in cyclicality of productivity, see section 1.1. Given that these observations are an important piece of evidence that may discriminate between various explanations suggested in the literature, I briefly discuss how the two mechanisms in my model are able to replicate these observations. I decompose the measured productivity in my model to the factor utilization component and the utilization-adjusted measured productivity and report the moments for the pre- and post-1984 period in table 11. Notice that the utilization-adjusted productivity in my model again consists of two components: the average technology level $Z$ and the effect of diminishing returns to labor. Table 11 also reports the moments for the isolated technology component $Z$.

The decomposition of the model variables confirms that both mechanisms comply with the observations from Fernald and Wang (2016). Firstly, utilization-adjusted TFP was never really pro-cyclical before the mid-1980s, and the correlation with inputs and output weakly increased after the mid-1980s. All three calibrations of my model generate countercyclical utility-adjusted productivity. The reason is that the main driving force of the fluctuations in aggregate output and hours is the aggregate demand shock, thus the effect of diminishing returns to labor dominates the true productivity changes. Lower volatility $\sigma_D$ generates slightly higher correlations (in absolute value), because the relative importance of the procyclical technology shocks increases. Secondly, factor utilization was the procyclical component of measured productivity before the mid-1980s and it stayed procyclical.[12] The model generates very high correlations of the utilization component with output and hours. Third, the relative volatility of the factor utilization compared to the utilization-adjusted productivity substantially decreased in the period after 1984. The major part of the vanishing cyclicality of measured productivity is explained by the decrease in the volatility of the utilization component. Both alternative choices of model parameters, reported in the second and third column of table 11, deliver a significant decrease in the relative volatility of the utilization component compared to the benchmark calibration. For more flexible hours, the utilization component becomes less volatile as firms and households adjust hours more easily and rely less on adjusting effort. In case of lower volatility of demand shocks, the fluctuations of utilization component decrease together with the fluctuations of hours, which increases the relative importance of the utilization-adjusted component.

# 7 Conclusion

In this paper I contribute to the discussion on the vanishing cyclicality of aggregate productivity by bringing in the industry-level evidence, which can help to discriminate between various explanations proposed in the literature. I first document the change in cyclical properties of productivity in the U.S. using industry-level data. I focus on a puzzling feature that the correlations of industry productivity with industry output and labor input remained on average much more stable before and after the mid-1980s compared to the aggregate correlations. The cyclical correlations of productivity decreased at the aggregate level, but much less at the industry level.

I construct a simple industry-level RBC model that can generate changes in the cyclical comovement of measured aggregate productivity and other macroeconomic variables through two distinct mechanisms. The procyclicality of aggregate productivity in the model, measured in terms of correlations with labor input and output, decreases when the relative size of aggregate demand side shocks decreases compared to technology shocks, as suggested, for example, in Barnichon (2010). The procyclicality of aggregate productivity also decreases when the observed labor input (hours) becomes more flexible in comparison to the unobserved labor input margin (effort), as suggested in Galí and van Rens (2019). I choose these two mechanisms from a wide variety of explanations proposed in the literature as the most likely candidates after considering the existing empirical evidence; e.g. Fernald and Wang (2016).

Although both mechanisms are able to reduce the correlations of aggregate productivity with output and labor input, I show that they have qualitatively different predictions for the cyclical properties of industry-level variables. Within my model framework, only the mechanism

[12] The correlation of the utilization measure with labor input actually decreased for brief periods between 1990 and 2005, but the effect is less important than the drop in the volatility of factor utilization.

based on a structural change in the composition of aggregate shocks is able to generate changes in aggregate correlations without generating counterfactual changes at the industry level.

Although a change in the composition of the two aggregate shocks in my model can generate a decrease in cyclicality of aggregate productivity, the change it can generate is smaller compared to the data. I acknowledge that the model with two types of aggregate shocks and no frictions is clearly too stylized to reflect the whole extent of the structural changes happening in the U.S. in the mid-1980s. The contribution of this paper is mostly in providing the intuition for why and how aggregate shocks can influence the moments at the aggregate and industry level in a different way. The simple model framework in this paper is well suited to provide the comparison between aggregate and industry-level second moments in an intuitive way. Nevertheless, there are limitations to how well the model can match the moments for the two subperiods. For a better match of pre- and post-1984 moments, and in order to answer the question of what kind of aggregate shocks are responsible for the changes in dynamic properties of productivity, a more complex model environment is necessary. Ideally, such a model should feature a more realistic industry structure, but also dynamic effects and nominal rigidities, which are important factors for generating the propagation of shocks across industries.

In addition to bringing a new piece of evidence to the rich literature on the vanishing cyclicality of labor productivity, I view a secondary contribution of the paper as a means of promoting the use of disaggregated data sets in macroeconomic research. The broadening gap between the available disaggregated data and the aggregate *macro* perspective offers new opportunities and challenges for researchers in the era of big data. In the first step, new and growing industry-level data sources such as the World Input-Output Database could be exploited more extensively to test existing macroeconomic theories.

## References


Acemoglu, D., V. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

Arias, A., G. Hansen, and L. Ohanian (2007, July). Why have business cycle fluctuations become less volatile? *Economic Theory 32*(1), 43–58.

Atalay, E. (2017, October). How Important Are Sectoral Shocks? *American Economic Journal: Macroeconomics 9*(4), 254–280.

Barnichon, R. (2010). Productivity and unemployment over the business cycle. *Journal of Monetary Economics 57*(8), 1013 – 1025.

Basu, S., J. G. Fernald, and M. S. Kimball (2006). Are technology improvements contractionary? *American Economic Review, American Economic Association 96*(5), 1418–1448.

Berger, D. (2018). Countercyclical restructuring and jobless recoveries. Manuscript.

Bernanke, B. S. (2009). On the outlook for the economy and policy: a speech at the Economic Club of New York, New York, New York, November 16, 2009. Speech 488, Board of Governors of the Federal Reserve System (U.S.).

Bils, M. and J.-O. Cho (1994, April). Cyclical factor utilization. *Journal of Monetary Economics 33*(2), 319–354.

Carvalho, V. and X. Gabaix (2013, August). The great diversification and its undoing. *American Economic Review 103*(5), 1697–1727.

Clarida, R., J. Galí, and M. Gertler (2000). Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory. *The Quarterly Journal of Economics 115*(1), 147–180.

Daly, M. C., J. G. Fernald, Ó. Jordá, and F. Nechio (2017). Shocks and Adjustments. Working Paper Series 2013-32, Federal Reserve Bank of San Francisco.

de Walque, G., H. Lundvall, D. Papageorgiou, J. Rysanek, D. Kulikov, P. Júlio, M. Lozej, D. Sideris, J. R. Maria, B. Micallef, S. Schmidt, V. Corbo, J. Hollmayr, S. Hurtado, T. Hledík, C. Thomas, J. Kilponen, M. Pisani, and M. Lemoine (2015). Comparing fiscal multipliers across models and countries in Europe. Working Paper Series 1760, European Central Bank.

Dupor, B. (1999). Aggregation and irrelevance in multi-sector models. *Journal of Monetary Economic 43*, 391–409.

Dynan, K. E., D. W. Elmendorf, and D. E. Sichel (2006, January). Can financial innovation help to explain the reduced volatility of economic activity? *Journal of Monetary Economics 53*(1), 123–150.

Evans, A. E. (2019, Apr). Average labour productivity dynamics over the business cycle. *Empirical Economics*.

Fernald, J. G. (2014). A Quarterly, Utilization-Adjusted Series on Total Factor Productivity. Working Paper Series 2012-19, Federal Reserve Bank of San Francisco.

Fernald, J. G. and J. C. Wang (2016, October). Why Has the Cyclicality of Productivity Changed? What Does It Mean? *Annual Review of Economics 8*(1), 465–496.

Foerster, A. T., P.-D. G. Sarte, and M. W. Watson (2011). Sectoral versus aggregate shocks: A structural factor analysis of industrial production. *Journal of Political Economy, University of Chicago Press 119*(1), 1–38.

Galí, J. (1999). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review 89*(1), 249–271.

Galí, J. and L. Gambetti (2009, January). On the sources of the great moderation. *American Economic Journal: Macroeconomics 1*(1), 26–57.

Galí, J., F. Smets, and R. Wouters (2012). Slow recoveries: A structural interpretation. *Journal of Money, Credit and Banking 44*, 9–30.

Galí, J. and T. van Rens (2019). The vanishing procyclicality of labor productivity. Manuscript.

Garin, J., M. J. Pries, and E. R. Sims (2018). The relative importance of aggregate and sectoral shocks and the changing nature of economic fluctuations. *American Economic Journal: Macroeconomics 10*(1), 119–48.

Holly, S. and I. Petrella (2012). Factor demand linkages, technology shocks, and the business cycle. *The Review of Economics and Statistics, MIT Press 94*(4), 948–963.

Horvath, M. (2000). Sectoral shocks and aggregate fluctuations. *Journal of Monetary Economic 45*, 69–106.

Hulten, C. R. (1978). Growth accounting with intermediate inputs. *Review of Economic Studies 45*(3), 511–518.

Jaimovich, N. and H. E. Siu (2012, August). Job polarization and jobless recoveries. Working Paper 18334, National Bureau of Economic Research.

Jorgenson, D. W. (2008). EU KLEMS. https://doi.org/10.7910/DVN/JJIB0J. UNF: 3:LF/zVBiYi3QdUFFjsXwB4w==, version V1.

Justiniano, A. and G. E. Primiceri (2008, June). The Time-Varying Volatility of Macroeconomic Fluctuations. *American Economic Review 98*(3), 604–641.

Kahn, J. A., M. M. McConnell, and G. Perez-Quiros (2002). On the causes of the increased stability of the U.S. economy. *Economic Policy Review* (May), 183–202.

KLEMS (2010). World klems data. Available at: `http://www.worldklems.net/`.

Lewis, V. J., S. Villa, and M. Wolters (2018). Labor productivity and inflation dynamics: the euro area vs the us.

McConnell, M. M. and G. Perez-Quiros (2000, December). Output fluctuations in the united states: What has changed since the early 1980's? *American Economic Review 90*(5), 1464–1476.

McGrattan, E. R. (2017, March). Intangible capital and measured productivity. Working Paper 23233, National Bureau of Economic Research.

McGrattan, E. R. and E. C. Prescott (2010, October). Unmeasured investment and the puzzling us boom in the 1990s. *American Economic Journal: Macroeconomics 2*(4), 88–123.

Nucci, F. and M. Riggi (2013). Performance pay and changes in U.S. labor market dynamics. *Journal of Economic Dynamics and Control 37*(12), 2796–2813.

Riggi, M. (2019, March). Capital Destruction, Jobless Recoveries, And The Discipline Device Role Of Unemployment. *Macroeconomic Dynamics 23*(02), 590–624.

Stiroh, K. J. (2009). Volatility accounting: a production perspective on increased economic stability. *Journal of the European Economic Association 7*(4), 671–696.

Timmer, M., T. van Moergastel, E. Stuivenwold, G. Ypma, M. O'Mahony, and M. Kangasniemi (2007, March). Eu klems growth and productivity accounts: Part 1 methodology. Methodology report, EUKLEMS consortium.

Timmer, M. P., M. O'Mahony, and B. van Ark (2007, Spring). EU KLEMS Growth and Productivity Accounts: An Overview. *International Productivity Monitor 14*, 71–85.

Wang, J. C. (2014). Vanishing procyclicality of productivity? industry evidence. Working Papers 14-15, Federal Reserve Bank of Boston.

Yépez, C. A. (2017). Financial intermediation, consumption dynamics, and business cycles. *Economic Modelling 60*, 231 – 243.

# A Data and construction of the moments

The primary data source that I use is the KLEMS growth accounting data set developed by Dale Jorgenson and his co-authors (Jorgenson 2008). The data set provides annual information on capital, labor and intermediate inputs and outputs of the U.S. economy between 1960 and 2005, disaggregated into 88 industries. This appendix describes in detail the construction of data series, aggregates, and data moments.

In line with the literature, I focus on the private business sector which consists of 77 industries. I aggregate the industry-level series of the private business sector to obtain the aggregate series. I exclude all government industries and the *Private households* industry. Government industries are usually omitted from productivity exercises because market prices are not available for government industries and are set arbitrarily. In my data, an additional problem with the government industries is that the information about intermediate inputs is often missing. In one case, a private industry (*59 Real estate - owner occupied dwellings*) does not utilize all inputs, as the only input is capital.

Table 12 lists the private sector industries and their relative shares in nominal output.

## A.1 Data inputs

### A.1.1 Gross output

Jorgenson database reports industry nominal gross output and producers price indexes normalized in 1996. Therefore, I express real gross output (and other real variables) in 1996 dollars. Aggregate real gross output is defined as the sum of real outputs across the 77 industries of the private business sector.

### A.1.2 Intermediate inputs

Real volumes of intermediate inputs can be expressed in 1996 dollars using the reported purchasers price index. I use Fisher price index in order to aggregate the real intermediate inputs delivered to a particular industry. This approach is consistent with the model economy, where the variety of intermediate inputs $m_{j,i,t}$ is aggregated into input $M_{i,t}$ according to a CES function.

Notice that gross output and intermediate input goods are not counted in consistent real units, as the two price indexes differ. Moreover, intermediate inputs reported in the database include imports, but the information about exports is not available. For these reasons, the goods market clearing identity at the industry level does not hold.

$$\text{gross output} \neq \text{consumption} + \text{investment} + \text{intermediate inputs}$$

The discrepancy is important for several reasons. First, value added can not be computed as a simple difference between gross output and intermediate inputs. Second, as we will see later, the measures of productivity are not comparable across industries.

### A.1.3 Labor input

The measure of labor input reported in the Jorgenson data set is effective hours. Effective hours are defined as total hours adjusted for the composition of workforce, taking into account basic observable characteristics (education, age and gender).

The Jorgenson database reports nominal costs of effective labor and a price index for each industry, which allow to compute the real labor input series. However, the units are not comparable across industries. For the sake of easier interpretation, I rescale the real labor input series to approximately reflect effective hours worked in each industry. I use the 72-industry version of EU KLEMS data (based on SIC classification of industries) as an additional data source in order to pin down the effective hours and hourly wages in each industry in 1996. I apply these wages to the labor costs information in the Jorgenson data set in order to express the real labor input in hours. The rescaling of labor input series does not affect the results, but has the advantage that it allows me to define aggregate hours as a sum of industry hours.

Although the two data sets are based on the same accounting principles, there are several issues with matching the EU KLEMS to Jorgenson KLEMS. I resolve these issues using ad-hoc rules which try to minimize the effect of the discrepancies.

- The level of disaggregation in some cases differs between the two datasets. In case several Jorgenson industries constitute a single EU KLEMS industry, I used the same wage level for all the industries. In one case a Jorgenson industry (*63 Business services excluding computer services*) corresponds to two EU KLEMS industries. I approximated the wage in this industry by a weighted average of wages in both the EU KLEMS industries. Some EU KLEMS service industries include both private and government sector, while I only focus on the private sector in the Jorgenson data. It is likely that the wages in the private and government sector differ, however, a large discrepancy is rather unlikely. In this case, I consider the wages reported in the EU KLEMS data set to apply for the private-sector industries in the Jorgenson data. In one case (*51 Water and sanitation*) the labor compensation and hours data in the EU KLEMS are missing. I use the wage information from the *50 Gas utilities* industry, which I consider to be the closest approximation.
- I chose 1996 as the base year for pinning down the industry-level wages in the EU KLEMS data. The results are robust with respect to the choice of base year.

### A.1.4 Capital accounts

Measuring the capital stock and capital services is typically the most challenging part of the growth accounting. Jorgenson database provides the nominal values and price index for the capital services in each industry. The KLEMS growth accounting is based on the assumption of perfect competition and zero profits. However, the nominal value of capital services is identified as the residual between value added and labor compensation. Therefore, it includes both the user cost of capital and profits.

The model abstracts from endogenous capital and assigns the non-labor income exclusively to firm profits. Since labor productivity is potentially affected by the fluctuations in capital services, it is more suitable to compare the model outcomes with measured total factor productivity.

### A.1.5 Value added

Because the data set does not allow to compute outputs and intermediate inputs in consistent real units, I can not compute industry real value added as a simple difference between the two series. I thus follow the standard growth accounting methodology and define real value added using the so-called *double deflation* method (Timmer et al. 2007). The method provides growth rates series of value added for each industry. Nevertheless, it does not provide level series in units that are consistent across industries. I define aggregate real value added as aggregate nominal value added divided by the Fisher price index associated with the industry-level prices.

| List of industries, private business sector, part 1 | | | |
|---|---|---|---|
| | | gross output nominal share | value added nominal share |
| 1 | Farms | 2.48 | 2.43 |
| 2 | Agricultural services, forestry | 0.37 | 0.35 |
| 3 | Fishing | 0.12 | 0.12 |
| 4 | Metal mining | 0.12 | 0.14 |
| 5 | Nonmetal mining | 0.15 | 0.21 |
| 6 | Coal mining | 0.26 | 0.39 |
| 7 | Oil and gas extraction | 1.52 | 1.90 |
| 8 | Construction | 7.04 | 6.65 |
| 9 | Lumber and wood | 0.89 | 0.69 |
| 10 | Furniture and fixtures | 0.53 | 0.49 |
| 11 | Nonmetallic mineral products | 0.76 | 0.83 |
| 12 | Primary metals | 1.68 | 1.39 |
| 13 | Fabricated metal production | 1.91 | 1.94 |
| 14 | Machinery excl. computers | 2.17 | 2.33 |
| 15 | Computers and office equipment | 0.76 | 0.45 |
| 16 | Insulated wire | 0.21 | 0.23 |
| 17 | Audio and video equipment | 0.12 | 0.09 |
| 18 | Other electrical machinery | 0.73 | 0.78 |
| 19 | Communications equipment | 0.46 | 0.45 |
| 20 | Electronic components | 0.78 | 0.61 |
| 21 | Motor vehicles | 2.64 | 1.22 |
| 22 | Aerospace | 1.13 | 1.22 |
| 23 | Ships and boats | 0.17 | 0.22 |
| 24 | Other transportation equipment | 0.17 | 0.15 |
| 25 | Measuring instruments | 0.62 | 0.67 |
| 26 | Medical equipment and opthalmic goods | 0.39 | 0.32 |
| 27 | Other instruments | 0.21 | 0.28 |
| 28 | Misc. manufacturing | 0.41 | 0.43 |
| 29 | Food | 3.99 | 2.33 |
| 30 | Tobacco | 0.23 | 0.19 |
| 31 | Textile | 0.70 | 0.63 |
| 32 | Apparel | 0.65 | 0.73 |
| 33 | Leather | 0.11 | 0.16 |
| 34 | Paper and allied | 1.28 | 1.05 |
| 35 | Publishing | 0.88 | 0.98 |
| 36 | Printing and reproduction | 0.68 | 0.72 |
| 37 | Chemicals excl. drugs | 2.39 | 1.98 |
| 38 | Drugs | 0.65 | 0.54 |
| 39 | Petroleum and coal products | 1.83 | 0.54 |
| 40 | Rubber and misc. plastics | 1.10 | 0.86 |

| | List of industries, private business sector, part 2 | | |
|---|---|---|---|
| | | gross output nominal share | value added nominal share |
| 41 | Railroad transportation | 0.43 | 0.75 |
| 42 | Local passenger transit | 0.22 | 0.40 |
| 43 | Trucking and warehousing | 1.75 | 1.83 |
| 44 | Water transportation | 0.34 | 0.34 |
| 45 | Air transportation | 0.83 | 0.67 |
| 46 | Transportation services and pipelines | 0.31 | 0.30 |
| 47 | Telephone and telegraph | 2.04 | 2.14 |
| 48 | Radio and TV | 0.53 | 0.39 |
| 49 | Electric utilities (pvt) | 2.05 | 2.28 |
| 50 | Gas utilities | 0.68 | 0.38 |
| 51 | Water and sanitation | 0.18 | 0.12 |
| 52 | Wholesale trade | 5.46 | 6.64 |
| 53 | Retail trade excl. motor vehicles | 4.40 | 5.78 |
| 54 | Retail trade, motor vehicles | 1.20 | 1.45 |
| 55 | Eating and drinking | 2.06 | 1.79 |
| 56 | Depository institutions | 2.74 | 2.40 |
| 57 | Nondeposit; Sec-com brokers; Investment | 1.76 | 1.51 |
| 58 | Insurance carriers, agents, services | 2.23 | 1.89 |
| 59 | Real Estate - owner occupied | 2.71 | 5.11 |
| 60 | Real Estate - other | 5.63 | 7.79 |
| 61 | Hotels | 0.77 | 0.88 |
| 62 | Personal services | 0.72 | 0.73 |
| 63 | Business services excl. computer | 2.48 | 2.70 |
| 64 | Computer services | 1.27 | 0.89 |
| 65 | Auto services | 1.01 | 0.86 |
| 66 | Misc. repair services | 0.42 | 0.58 |
| 67 | Motion pictures | 0.40 | 0.29 |
| 68 | Recreation services | 0.80 | 0.70 |
| 69 | Offices of health practitioners | 2.12 | 2.20 |
| 70 | Nursing and personal care facilities | 0.46 | 0.43 |
| 71 | Hospitals, private | 2.00 | 1.87 |
| 72 | Health services, nec | 0.53 | 0.47 |
| 73 | Legal services | 1.06 | 1.12 |
| 74 | Educational services (private) | 0.81 | 0.78 |
| 75 | Social services and membership org. | 1.49 | 1.34 |
| 76 | Research | 0.42 | 0.37 |
| 77 | Misc professional services | 2.38 | 2.11 |

Table 12: List of private industries, Jorgenson and coauthors. Percentage shares of industry nominal gross output and value added in total gross output and value added, average for 1960-2005.

## A.2 Measuring productivity

I rely on the standard KLEMS methodology (Timmer et al. 2007) for computing the two standard measures of productivity: labor productivity and TFP. I define the measured labor productivity as value added per effective hour and measured TFP as the usual Solow residual.

Industry accounts of the KLEMS type are based on the assumptions of perfectly measurable factor inputs, constant returns to scale and perfect competition, such that the factors are paid their marginal products. In the model, however, firms make profits and factor utilization is not measurable. Therefore, the standard Solow residual formulas used in productivity accounting deviate from the true technology in the model. Measured TFP is influenced not only by technology shocks, but also by changes in demand. At industry level, I compute the Solow residuals following the methodology of the EU KLEMS database as

$$T\hat{FP}m_{it} = \hat{va}_{it} - s^L_{it}\hat{h}_{it} - s^K_{it}\hat{k}_{it}, \tag{43}$$

where $s^X$ is the cost share of input $X$ in value added and hats denote growth rates of variables. I refer to $TFPm$ as *measured productivity.* I choose to report value added-based TFP over gross output-based TFP at both aggregate and industry level because they are directly comparable with their model counterparts. The difference between the two measures is only in rescaling the productivity series by the share of cost share of value added in the gross output.[13]

The true technology in my model can be expressed as

$$A_t\hat{z}_{it} = \hat{va}_{it} - s^L_{it}(\hat{h}_{it} + \hat{e}_{it}) - s^K_{it}\hat{k}_{it}, \tag{44}$$

where the last term drops out in case of constant capital input. The technology is only equivalent to measured productivity (eq. 43) in the case of constant effort.

Moreover, the levels of measured productivity are not comparable across industries, as value added and inputs are not counted in consistent units. In line with the KLEMS methodology, I define *measured aggregate TFP* using aggregate measures of inputs and output as

$$T\hat{FP}m_t = \hat{VA} - s^H_t\hat{H}_t - s^K_t\hat{K}_t. \tag{45}$$

For all variables I always use the same procedure to construct them in the data and from the model simulations.

## A.3 Moments

Correlations between productivity and other aggregate variables and their standard deviations are computed using the series described in the main text. Cross-industry weighted averages of industry-level correlations and standard deviations are computed using nominal output shares as weights. The benchmark weighting is based on the industries' average nominal output share in the first sub-period. I compute the cross-industry second moments using alternative weights in order to check the robustness of the results.

[13] $T\hat{FP}m_{it} = \hat{va}_{it} - s^L_{it}\hat{h}_{it} - s^K_{it}\hat{k}_{it} - s^L_{it}\hat{h}_{it} = \frac{1}{s^{VA}_{it}}\left(\hat{y}_{it} - s^K_{it}\hat{k}_{it} - s^L_{it}\hat{l}_{it} - s^M_{it}\hat{M}_{it}\right) = \frac{1}{s^{VA}_{it}} T\hat{FP}m^{GO}_{it}$,

Standard deviation of measured value added and productivity in two of the industries in the data sample is extremely volatile. Both industries (*39 Petroleum and coal products* and *50 Gas utilities*) are likely to be affected by extremely volatile prices of their intermediate inputs, especially in the first sub-period. Because these extreme values affect the averages disproportionally and can not be captured by the model with ex ante homogeneous industries, I winsorize the standard deviations at the maximum value across the remaining industries for each variable.

# B Additional empirical evidence

### B.0.1 Comparison to previous studies

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

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

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

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

Figure 5: Aggregate correlations pre- and post-1984 in Wang (2014).

Table 1. The Vanishing Procyclicality of Labor Productivity

| | Corr with output | | | Corr with labor input | | |
|---|---|---|---|---|---|---|
| | Pre-84 | Post-85 | Change | Pre-84 | Post-85 | Change |
| Output per hour | | | | | | |
| BP | 0.63 | 0.07 | −0.55 | 0.23 | −0.41 | −0.64 |
| | [0.05] | [0.08] | [0.10] | [0.08] | [0.07] | [0.11] |
| 4D | 0.65 | 0.18 | −0.47 | 0.18 | −0.42 | −0.60 |
| | [0.05] | [0.09] | [0.10] | [0.07] | [0.09] | [0.11] |
| HP | 0.64 | −0.09 | −0.72 | 0.21 | −0.55 | −0.77 |
| | [0.05] | [0.09] | [0.10] | [0.07] | [0.07] | [0.10] |
| Output per worker | | | | | | |
| BP | 0.78 | 0.51 | −0.27 | 0.29 | −0.11 | −0.39 |
| | [0.03] | [0.07] | [0.07] | [0.08] | [0.09] | [0.12] |
| 4D | 0.77 | 0.44 | −0.33 | 0.19 | −0.20 | −0.40 |
| | [0.03] | [0.08] | [0.08] | [0.07] | [0.12] | [0.14] |
| HP | 0.77 | 0.32 | −0.45 | 0.24 | −0.29 | −0.53 |
| | [0.03] | [0.09] | [0.09] | [0.07] | [0.09] | [0.11] |

Table 2. The Rising Volatility of Labor Input

| | Std. Dev. | | | Relative Std. Dev. | | |
|---|---|---|---|---|---|---|
| | Pre-84 | Post-85 | Ratio | Pre-84 | Post-85 | Ratio |
| Hours (private sector) | | | | | | |
| BP | 2.02 | 1.52 | 0.75 | 0.80 | 1.09 | 1.37 |
| | [0.10] | [0.09] | [0.06] | [0.03] | [0.04] | [0.07] |
| 4D | 3.05 | 2.43 | 0.80 | 0.77 | 1.08 | 1.40 |
| | [0.16] | [0.27] | [0.10] | [0.03] | [0.06] | [0.10] |
| HP | 2.04 | 1.76 | 0.86 | 0.79 | 1.20 | 1.52 |
| | [0.10] | [0.10] | [0.07] | [0.03] | [0.05] | [0.09] |
| Employment (private sector) | | | | | | |
| BP | 1.66 | 1.20 | 0.72 | 0.66 | 0.87 | 1.32 |
| | [0.08] | [0.07] | [0.06] | [0.03] | [0.05] | [0.09] |
| 4D | 2.58 | 2.06 | 0.80 | 0.65 | 0.92 | 1.41 |
| | [0.13] | [0.23] | [0.10] | [0.03] | [0.06] | [0.11] |
| HP | 1.72 | 1.46 | 0.85 | 0.66 | 0.99 | 1.50 |
| | [0.09] | [0.08] | [0.07] | [0.03] | [0.06] | [0.11] |

Figure 6: Aggregate correlations and volatility pre- and post-1984 in Galí and van Rens (2019).

### B.0.2 Robustness of industry-level correlations

| | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| **corr(TFP, GDP)** | | | | |
| First Diff. | 0.80 | 0.81 | 0.79 | -0.02 |
| | [0.02] | [0.01] | [0.03] | [0.04] |
| CF | 0.82 | 0.81 | 0.84 | 0.03 |
| | [0.01] | [0.01] | [0.02] | [0.03] |
| HP par=100 | 0.78 | 0.79 | 0.76 | -0.04 |
| | [0.03] | [0.02] | [0.07] | [0.09] |
| HP par=6.25 | 0.81 | 0.81 | 0.81 | 0.01 |
| | [0.01] | [0.02] | [0.03] | [0.04] |
| **corr(TFP, H)** | | | | |
| First Diff. | -0.10 | 0.00 | -0.21 | -0.21 |
| | [0.05] | [0.05] | [0.05] | [0.09] |
| CF | -0.02 | 0.08 | -0.11 | -0.19 |
| | [0.04] | [0.05] | [0.03] | [0.06] |
| HP par=100 | -0.14 | -0.03 | -0.27 | -0.24 |
| | [0.06] | [0.07] | [0.05] | [0.10] |
| HP par=6.25 | -0.06 | 0.05 | -0.17 | -0.22 |
| | [0.05] | [0.06] | [0.03] | [0.08] |
| **corr(LP, GDP)** | | | | |
| First Diff. | 0.73 | 0.73 | 0.71 | -0.02 |
| | [0.02] | [0.02] | [0.03] | [0.04] |
| CF | 0.72 | 0.71 | 0.74 | 0.02 |
| | [0.02] | [0.02] | [0.03] | [0.04] |
| HP par=100 | 0.72 | 0.71 | 0.70 | -0.01 |
| | [0.03] | [0.03] | [0.07] | [0.08] |
| HP par=6.25 | 0.72 | 0.71 | 0.71 | 0.00 |
| | [0.02] | [0.02] | [0.04] | [0.04] |
| **corr(LP, H)** | | | | |
| First Diff. | -0.30 | -0.22 | -0.40 | -0.18 |
| | [0.04] | [0.05] | [0.04] | [0.08] |
| CF | -0.23 | -0.13 | -0.32 | -0.19 |
| | [0.04] | [0.05] | [0.03] | [0.07] |
| HP par=100 | -0.32 | -0.22 | -0.42 | -0.21 |
| | [0.05] | [0.06] | [0.04] | [0.09] |
| HP par=6.25 | -0.27 | -0.16 | -0.38 | -0.21 |
| | [0.05] | [0.06] | [0.03] | [0.07] |

Table 13: [Table 3 with standard errors] Average industry-level cyclical correlations between selected productivity measures and output, resp. hours. Weighted averages using constant industry weights over time: average nominal output share between 1960 and 1983. Comparison pre- and post-1984. Standard errors computed using bootstrapping (re-sampling the series 800 times using 6 years blocks).

| | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| **corr(TFPm, GDP)** | | | | |
| First Diff. | 0.76 | 0.77 | 0.73 | -0.04 |
| CF | 0.78 | 0.77 | 0.78 | 0.00 |
| HP par=100 | 0.75 | 0.75 | 0.71 | -0.04 |
| HP par=6.25 | 0.77 | 0.77 | 0.75 | -0.01 |
| **corr(TFPm, H)** | | | | |
| First Diff. | -0.14 | -0.03 | -0.25 | -0.22 |
| CF | -0.08 | 0.02 | -0.19 | -0.21 |
| HP par=100 | -0.14 | -0.04 | -0.25 | -0.21 |
| HP par=6.25 | -0.10 | 0.01 | -0.21 | -0.22 |
| **corr(LP, GDP)** | | | | |
| First Diff. | 0.74 | 0.76 | 0.68 | -0.08 |
| CF | 0.74 | 0.74 | 0.72 | -0.02 |
| HP par=100 | 0.73 | 0.74 | 0.67 | -0.06 |
| HP par=6.25 | 0.74 | 0.74 | 0.70 | -0.04 |
| **corr(LP, H)** | | | | |
| First Diff. | -0.33 | -0.23 | -0.43 | -0.20 |
| CF | -0.29 | -0.19 | -0.39 | -0.20 |
| HP par=100 | -0.32 | -0.24 | -0.41 | -0.18 |
| HP par=6.25 | -0.30 | -0.21 | -0.40 | -0.20 |

Table 14: Average industry-level cyclical correlations between selected productivity measures and output, resp. hours. Robustness: simple averages, unit industry weights. Comparison pre- and post-1984. Each correlation is computed using four different detrending methods.

# C Bottom-up construction of aggregate series

## C.1 Time-varying industry weights

### C.1.1 Approximation formulas

Let us assume that the aggregate variable $X_t$ can be expressed (exactly) as

$$X_t = \sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t}, \tag{46}$$

where $x_{it}$ are the industry level series and $\hat{w}_{it}$ are time varying weights. Then, for the growth rate of the aggregate variable it follows that

$$\begin{aligned}
\tilde{X}_{t+1} &= \frac{X_{t+1} - X_t}{X_t} \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t+1} x_{i,t+1} - \sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t+1} x_{i,t+1} - \sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t+1} + \sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t+1} - \sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t}(x_{i,t+1} - x_{i,t}) + \sum_{i=1}^{N}(\hat{w}_{i,t+1} - \hat{w}_{i,t}) x_{i,t+1}\right) \\
&= \frac{1}{X_t}\left(\sum_{i=1}^{N} \hat{w}_{i,t} x_{i,t} \tilde{x}_{i,t+1} + \sum_{i=1}^{N} \tilde{w}_{i,t+1} \hat{w}_{i,t} x_{i,t+1}\right) \\
&= \sum_{i=1}^{N} w_{i,t+1} \tilde{x}_{i,t+1} + \sum_{i=1}^{N} \tilde{w}_{i,t+1} \frac{\hat{w}_{i,t} x_{i,t+1}}{X_t},
\end{aligned}$$

where $\tilde{x}_{i,t}$ is the growth rate between periods $t$ and $t-1$ of industry-level variable $x_i$, $\tilde{w}_{i,t+1}$ is the growth rate of weight $\hat{w}_i$ and where in the last equation we have defined

$$w_{i,t+1} = \frac{\hat{w}_{i,t} x_{i,t}}{X_t}.$$

Notice that if the growth rate of weights $\tilde{w}_{i,t+1}$ is small, the second term is negligible and we obtain expression

$$\tilde{X}_t \approx \sum_{i=1}^{N} w_{i,t} \tilde{x}_{i,t}. \tag{47}$$

#### C.1.2 Weights

For gross output, value added, capital, hours and industry-level total intermediate inputs, the aggregate nominal value is the sum of industry nominal values. Thus, I can substitute into equation 46 directly with

$$X_t^{real} = \sum_{i=1}^{N} \frac{p_{i,t}^x}{P_t^X} x_{i,t}^{real}, \tag{48}$$

where $x_i$ is the industry variable of interest, $p_{i,t}^x$ is the price of $x_{i,t}$ and $P_t^X$ is the corresponding price index. It follows that I can substitute into 46 and 47

$$\hat{w}_{it} = \frac{p_{i,t}^x}{P_t^X}, \tag{49}$$

$$w_{i,t+1} = \frac{p_{i,t}^x x_{i,t}}{P_t^X X_t}. \tag{50}$$

Notice that $w_{i,t+1}$ is the nominal cost share of industry $i$ at time $t$.

| Variable | Flex. weights rel. std. dev. | Constant weights relative std. dev. sample mean | pre-1984 mean |
|---|---|---|---|
| Value added | 1.00 | 0.97 | 1.04 |
| Gross output | 1.00 | 0.98 | 1.04 |
| Measured TFP | 1.00 | 0.91 | 0.98 |
| Labor productivity | 1.00 | 0.94 | 1.01 |
| Hours | 1.00 | 1.02 | 1.05 |
| Capital | 1.00 | 1.12 | 1.08 |
| Inter. inputs | 1.00 | 1.00 | 1.02 |

Table 15: Relative standard deviations of weighted averages compared to the original aggregate series. Weighted averages constructed using flexible time-varying weights and constant weights (sample mean and pre-1984 mean weights).

For labor productivity it is straightforward to derive that

$$LP_t = \frac{VA_t}{H_t} = \frac{\sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} va_{i,t}}{H_t} \tag{51}$$

$$= \sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{va_{i,t}}{h_{i,t}} \frac{h_{i,t}}{H_t} \tag{52}$$

$$= \sum_{i=1}^{N} \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{h_{i,t}}{H_t} lp_{i,t}. \tag{53}$$

Therefore, I can substitute in equations 46 and 47 with

$$\hat{w}_{i,t} = \frac{p_{i,t}^{VA}}{P_t^{VA}} \frac{h_{i,t}}{H_t} \tag{54}$$

$$w_{i,t+1} = \frac{p_{i,t}^{VA} va_{i,t}}{P_t^{VA} VA_t}. \tag{55}$$

For measured TFP, I follow Hulten (1978) and use Domar weights for aggregating gross-output based industry total factor productivity into value-added based aggregate series, which gives me

$$w_{i,t+1} = \frac{p_{i,t} y_{i,t}}{P_t^{VA} VA_t}, \tag{56}$$

where $y_i$ stands for industry gross output and $VA$ stands for aggregate value added.

### C.1.3 Quality of approximation

To assess the quality of approximation of the aggregate series by the bottom-up formulas I plot the comparison of different versions of the aggregate series in figure 7. The quality of approximation by the formula with time-varying weights is very good. Table 15 reports the relative standard deviation of weighted average series compared to the original aggregate series. The relative standard deviation is very close to one for each of the series.

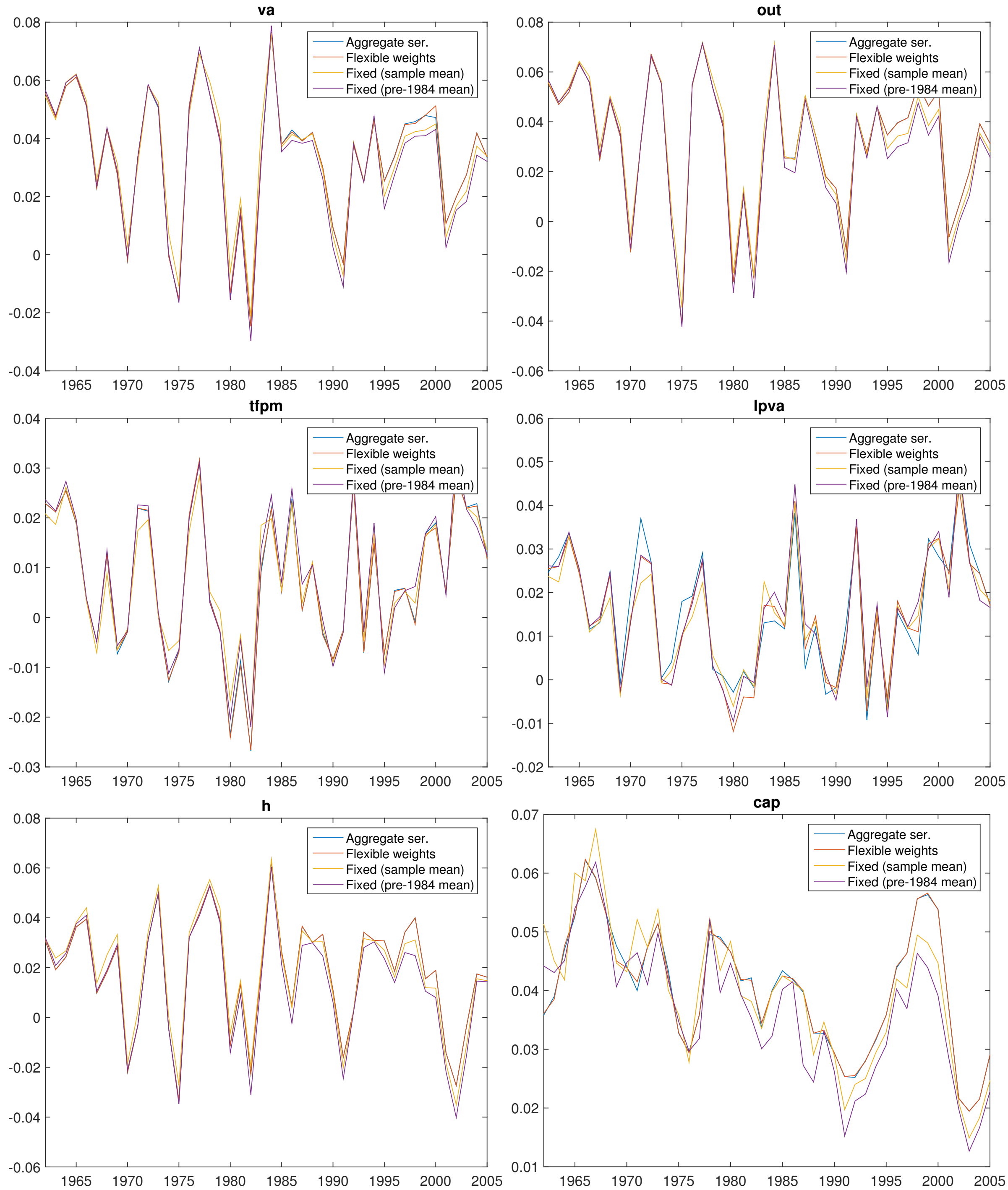


Figure 7: Comparison between aggregate series and weighted averages: value added ($VA$), gross output ($OUT$), measured TFP ($TFPm$), labor productivity ($LP$), hours ($H$) and capital ($CAP$). *Flexible weights* denote the series constructed using time-varying industry weights. *Fixed* series are plotted for two alternative weighing options - based on the whole sample and pre-1984 mean weights.

| | 1960-2005 | 1960-1983 | 1984-2005 | Difference |
|---|---|---|---|---|
| **corr(TFPm, GDP)** | | | | |
| First Diff. | 0.70 | 0.83 | 0.51 | -0.32 |
| CF | 0.82 | 0.81 | 0.65 | -0.16 |
| HP par=100 | 0.68 | 0.81 | 0.35 | -0.45 |
| HP par=6.25 | 0.75 | 0.79 | 0.47 | -0.32 |
| **corr(TFPm, H)** | | | | |
| First Diff. | 0.22 | 0.53 | -0.19 | -0.72 |
| CF | 0.47 | 0.52 | 0.04 | -0.48 |
| HP par=100 | 0.21 | 0.54 | -0.28 | -0.82 |
| HP par=6.25 | 0.36 | 0.49 | -0.15 | -0.64 |
| **corr(LP, GDP)** | | | | |
| First Diff. | 0.43 | 0.60 | 0.27 | -0.33 |
| CF | 0.54 | 0.59 | 0.25 | -0.33 |
| HP par=100 | 0.49 | 0.60 | 0.28 | -0.32 |
| HP par=6.25 | 0.46 | 0.55 | 0.14 | -0.41 |
| **corr(LP, H)** | | | | |
| First Diff. | -0.13 | 0.22 | -0.46 | -0.67 |
| CF | 0.09 | 0.22 | -0.41 | -0.63 |
| HP par=100 | -0.05 | 0.27 | -0.40 | -0.67 |
| HP par=6.25 | -0.02 | 0.18 | -0.50 | -0.68 |

Table 16: Fixed industry composition over time: Cyclical correlation between selected productivity measures and output/hours. Aggregate series using constant industry weights (mean over 1960-1983).

### C.2 Constant weights

The constant-weight or fixed-weight aggregate series are weighted averages defined as

$$\tilde{X}_t \approx \sum_{i=1}^{N} \bar{w}_i \tilde{x}_{i,t}, \tag{57}$$

where constant weights $\bar{w}_i$ are averages over weights $w_{i,t}$ defined in the previous section. The benchmark weights are average shares over the pre-1984 period. The results are very robust with respect to different choice od weights.

Figure 7 plots the comparison of fixed-weight series to the original aggregate series. The fixed-weight series are still a very good approximation, although some differences are visible especially for capital. Second and third column of table 15 report the relative standard deviation of the fix-weight aggregate series compared to the aggregate series. For all variables with the exception of capital, the relative volatility is closer than 5% away from the aggregate series.

Table 16 reports the correlation between selected variables computed using the fixed-weight aggregate series for all detrending methods.

# D Robustness exercises

In each of the robustness exercises, parameter $\epsilon$ and the volatilities of all types of shocks are recalibrated such that the targets listed in section 4.1 are matched.

## D.1 Elasticity of substitution $\sigma = 0.5$

| **Aggregate** | correlation productivity with output | with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.83 | 0.53 | 0.89 | 0.028 |
| Post-1984 | 0.51 | -0.19 | 1.20 | 0.018 |
| **Model** | | | | |
| Benchmark calibration | 0.67 | 0.53 | 0.88 | 0.028 |
| Flexible hours | -0.05 | -0.19 | 1.02 | 0.032 |
| Smaller dem. shocks | 0.59 | 0.34 | 0.86 | 0.017 |

Table 17: Selected aggregate second moments, alternative value of the elasticity of substitution $\sigma = 0.5$. Data (top panel) and model simulations (bottom panel).

| **Industry** | correlation productivity with output | with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.81 | 0.00 | 0.63 | 0.080 |
| Post-1984 | 0.79 | -0.21 | 0.57 | 0.076 |
| **Model** | | | | |
| Benchmark calibration | 0.54 | 0.25 | 0.87 | 0.083 |
| Flexible hours | 0.12 | -0.17 | 1.01 | 0.091 |
| Smaller dem. shocks | 0.54 | 0.24 | 0.87 | 0.080 |

Table 18: Selected averages of industry-level second moments, alternative value of the elasticity of substitution $\sigma = 0.5$. Data (top panel) and model simulations (bottom panel).

### D.2 Elasticity $\rho = 0.5$

| **Aggregate** | correlation productivity with output | with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.83 | 0.53 | 0.89 | 0.028 |
| Post-1984 | 0.51 | -0.19 | 1.20 | 0.018 |
| **Model** | | | | |
| Benchmark calibration | 0.66 | 0.53 | 0.89 | 0.028 |
| Flexible hours | -0.06 | -0.19 | 1.02 | 0.032 |
| Smaller dem. shocks | 0.59 | 0.39 | 0.88 | 0.018 |

Table 19: Selected aggregate second moments, alternative value of the intertemporal elasticity $\rho = 0.5$. Data (top panel) and model simulations (bottom panel).

| **Industry** | correlation productivity with output | with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.81 | 0.00 | 0.63 | 0.080 |
| Post-1984 | 0.79 | -0.21 | 0.57 | 0.076 |
| **Model** | | | | |
| Benchmark calibration | 0.56 | 0.27 | 0.86 | 0.076 |
| Flexible hours | 0.18 | -0.11 | 0.99 | 0.085 |
| Smaller dem. shocks | 0.56 | 0.26 | 0.86 | 0.073 |

Table 20: Selected averages of industry-level second moments, alternative value of the intertemporal elasticity of substitution $\rho = 0.5$. Data (top panel) and model simulations (bottom panel).

## D.3 Frisch elasticity of labor supply $\eta^{Frisch} = 1$

| **Aggregate** | correlation with output | productivity with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.83 | 0.53 | 0.89 | 0.028 |
| Post-1984 | 0.51 | -0.19 | 1.20 | 0.018 |
| **Model** | | | | |
| Benchmark calibration | 0.65 | 0.53 | 0.89 | 0.028 |
| Flexible hours | -0.05 | -0.19 | 1.02 | 0.030 |
| Smaller dem. shocks | 0.59 | 0.39 | 0.88 | 0.019 |

Table 21: Selected aggregate second moments, alternative value of the Frisch elasticity of labor supply $\eta^{Frisch} = 1$. Data (top panel) and model simulations (bottom panel).

| **Industry** | correlation with output | productivity with hours | rel. std.dev. hours | std.dev. output |
|---|---|---|---|---|
| **Data** | | | | |
| Pre-1984 | 0.81 | 0.00 | 0.63 | 0.080 |
| Post-1984 | 0.79 | -0.21 | 0.57 | 0.076 |
| **Model** | | | | |
| Benchmark calibration | 0.56 | 0.29 | 0.86 | 0.081 |
| Flexible hours | 0.17 | -0.11 | 0.99 | 0.087 |
| Smaller dem. shocks | 0.56 | 0.28 | 0.86 | 0.078 |

Table 22: Selected averages of industry-level second moments, alternative value of the Frisch elasticity of labor supply $\eta^{Frisch} = 1$. Data (top panel) and model simulations (bottom panel).

# E Additional analytical results

## E.1 Analytical derivation of corr(Y,LP)

At the industry level, the correlation between measured productivity and output can be expressed as (for the elasticity of substitution $\sigma$ equals one):

$$\mathrm{Corr}(\tilde{lp}_i, \tilde{y}_i) = \frac{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma B}{\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + \Gamma^2}\sqrt{\frac{\mathrm{Var}(\tilde{z}_i)}{\mathrm{Var}(\tilde{h}_i)} + B^2}}. \tag{58}$$

Equation 58 expresses the correlation in terms of two factors: the parameter $\Gamma$ (resp. $B = \Gamma + 1$) and the relative variance of industry technology $\tilde{z}_i$ and hours $\tilde{h}_i$.

For the aggregate variables, it follows that (for the case when the elasticity $\rho$ equals one):

$$\mathrm{Corr}(\tilde{LP}, \tilde{Y}) = \frac{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + \Gamma B}{\sqrt{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + \Gamma^2}\sqrt{\frac{\mathrm{Var}(\tilde{Z})}{\mathrm{Var}(\tilde{H})} + B^2}}. \tag{59}$$

In equations 58 and 59, the exogenous shocks only influence the variance ratios. The corner case in which the variance ratio approaches infinity implies unit correlation. Coefficient $\Gamma$ determines the sign of the correlation. For positive values of $\Gamma$, also the other corner case in which the variance ratio is equal to zero implies unit correlation. Between the two corner cases, the correlation decreases but can not switch signs. In fact, it can be shown that the correlation is higher or equal to a positive constant $c^{\Gamma} = \frac{2\sqrt{B\Gamma}}{B+\Gamma}$ for any positive value of the variance ratio.

The comparison of equations 58 and 59 delivers the key insights analogous to section 5.

## E.2 Frisch elasticity of labor supply

As there are different margins of labor input in my model, I also have several differing concepts of the labor supply elasticity. In what follows, I derive a measure that closely resembles the standardly used Frisch elasticity of labor supply.

Using the functional form 15, equation 25 can be reformulated as

$$D w_i C^{-\rho} = \Theta h_i^{\frac{\epsilon\eta}{1+\epsilon}}, \tag{60}$$

where $\Theta$ is a constant. Thus, at the industry level, Frisch elasticity can be expressed as

$$EL^{Frisch} = \frac{1}{\eta^{Frisch}} = \frac{1+\epsilon}{\epsilon\eta} = \frac{1}{\eta}\left(1 + \frac{1}{\epsilon}\right) > \frac{1}{\eta} \tag{61}$$

Since the elasticity is the same in all industries, it also apply to the aggregate labor supply.