The Productivity Puzzle and the Decline of Unions

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Abstract
For nearly four decades in the post-War United States, average labour productivity and total factor productivity remained procyclical — falling during recessions and rising in booms. Productivity puzzle refers to the sudden vanishing of this procyclicality of productivity during the mid-1980s. This paper argues that increased labour market flexibility, as manifest in rapid de-unionization, can help explain the puzzle. Declining costs of hiring and firing workers due to the fall in union power prompted firms to rely more on employment adjustment instead of intensive margin changes in workers’ effort through labour hoarding. Since labour hoarding explained procyclicality of productivity historically, lower dependence on it in recent decades made measured productivity less procyclical. Cross-sectional evidence from U.S. states and industries, as well as the changing responses of the aggregate U.S. economy to technology and demand shocks, bear out this mechanism. Allowing the hiring cost to change between pre and post-1980s in an otherwise standard New Keynesian model with endogenous effort is shown to match the empirical patterns in productivity moments quite well.

Keywords: labour productivity, unions, hiring cost, factor utilization, DSGE model

JEL Codes: E22, E23, E24, E32, O47

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1 Introduction

For almost half a century after World War II, labour productivity was procyclical in the U.S. — it rose during booms and fell in recessions. However, since the mid-1980s, it became acyclical with output and countercyclical with total hours worked.\(^1\) Quite strikingly, during the recent Great Recession of the late 2000s, while output and hours took a downward turn, labour productivity stayed constant or even increased slightly over some quarters (Mulligan, 2011). This change in the cyclical correlations has been well documented, and is often referred to as the ‘labour productivity puzzle’ (McGrattan and Prescott, 2012).\(^2\) Acknowledging the importance of its implications for jobless recoveries and slower productivity growth after recent recessions, this paper attempts to provide a comprehensive understanding of the forces behind the puzzle.

Typically, the explanation for procyclical labour productivity has been the phenomenon of ‘labour hoarding’\(^3\), whereby firms use their available workers less intensely during economic downturns, and more intensely during booms. Since such changes in the intensity of factor utilization cannot be observed in the changes of actual employment or labour hours, the measured labour productivity, which is defined as output per hour worked, appears to be procyclical.\(^4\) Therefore, when the procyclicality of labour productivity started to diminish in the mid-1980s, a natural candidate for explanation was the vanishing procyclicality of factor utilization. Now, firms resorted to labour hoarding because it was costly for them to hire and fire workers along the business cycle. Therefore, any explanation for reduced labour hoarding should involve more flexible labour market institutions which brings down the cost of employment adjustment. Such reduction in hiring frictions can also explain the steady increase in the volatility of employment relative to that of output since the mid-1980s. This paper identifies rapid de-unionization since the early 1980s as a key factor behind increased labour market flexibility in the U.S. that made hiring and firing workers easier for firms. In a cross-section of U.S. states and industries, the magnitude of decline in union density is shown to be significantly correlated with the drop in labour productivity correlations and the rise in the relative volatility of employment. Other structural changes in the labour market like the increased use of part-time workers, and the rise in online job search market do not appear to have caused the drop in productivity correlations. I also do not find evidence for the rise of the service sector, increased inter-sectoral reallocation of

\(^1\)The level of correlation depends on the choice of the filtering process to extract the cyclical part of the variation from raw time-series data, but the fall in correlations is robust.

\(^2\)In popular media, the term productivity puzzle has recently been used in different contexts to mean a variety of phenomena in the U.S. economy, e.g., the slow growth of productivity in recent years, the divergence between labour productivity and real wage growth, etc. However, most of the academic literature recognizes the vanishing procyclicality of productivity as the ‘productivity puzzle’, and it is in this sense that the term will be used in this paper.

\(^3\)Biddle (2014) notes that the concept of ‘labour hoarding’, at least in its modern form, dates back to Okun (1962). By the 1980s, the concept was being regularly used as a standard textbook explanation for procyclical labour productivity (e.g., Dornbusch and Fischer (1981), Hamermesh and Rees (1984)). Paradoxically, it was around the same time that labour productivity started being more countercyclical.

\(^4\)Real business cycle (RBC) models differ on the explanation of productivity procyclicality. They argue that business cycles are driven by procyclical technology shocks. In Section 2.2.2, I show evidence of negative response of labour inputs to positive technology shocks, which militates against the RBC paradigm.
employment, or the increased use of intangible capital in production to be a significant contributing factor for the vanishing procyclicality of productivity.

Declining hiring costs should be accompanied by changes in how the economy responds to different types of shocks. For example, in response to a positive demand shock, firms can now increase their labour input by hiring more workers, and hence do not need to increase the intensity of labour utilization by as much. This would in turn imply that the improvement in measured labour productivity and total factor productivity (TFP) in response to a positive demand shock will be significantly reduced. In fact, using a time-varying structural VAR analysis, I show that this is indeed the case. However, I find other structural changes in the response of the U.S. economy to shocks, which counteracts the drop in labour productivity correlations. For example, in response to a positive technology shock, per-capita hours worked decline by much less on impact in the post-1984 era than in the pre-1984 period. While this can be due to various factors like a more accommodating monetary policy by the Federal Reserve in the Great Moderation era, it nevertheless tends to increase the cyclical correlation between productivity and hours in the post-1984 period. Thus, it becomes important to ascertain the relative quantitative importance of such opposing forces in explaining the observed changes in cyclical productivity correlations through a more structural model.

The paper uses a standard New Keynesian model with only two shocks, (namely, a technology shock to TFP, and a demand shock to monetary policy) and incorporates endogenous movements in labour effort or utilization with costly hiring of workers by firms. This allows one to discuss not only the role of the fall in hiring frictions due to de-unionization, but also bring forth the quantitative role played by the changing nature of technology and demand shocks in explaining the labour productivity puzzle. Reasonable calibration of the model can generate almost the entire drop in productivity correlations, more than half of the rise in relative volatility of employment, and almost all of the changes in the correlations of productivity conditional on technology and demand shocks.

Finally, the link between the diminishing procyclicality of labour productivity and jobless recoveries cannot be overlooked. The last three recessions in the U.S. (since the early 1990s recession) were characterized by recoveries where output and productivity picked up (albeit at a slower pace than previous recessions) but labour input did not rise in the initial recovery phase. This phenomenon has been termed as jobless recoveries. Even though jobless recoveries correspond to only a fraction of the entire business cycle (namely, the post-recession recovery and not the pre-recession boom or the recession itself), they are clearly consistent with the falling correlation between productivity and labour input. However, jobless recoveries are at odds with the falling correlation between output and productivity. Nevertheless, it is natural to ask whether factors explaining the vanishing procyclicality of measured productivity can also explain the phenomenon of jobless recoveries, and the current paper will investigate this aspect too.
Contribution in light of related literature

The present work primarily relates to the literature on the causes of vanishing procyclicality of labour productivity. So far, two major strands of explanations have been proposed. One branch focuses on some form of mismeasurement. McGrattan and Prescott (2012) stress the under-estimation of intangible capital, while Galí and van Rens (2017) point out that a crucial role has been played by the unmeasured effort-level or intensity of labour. The other strand of the literature focuses on the changing nature of various kinds of shocks to the economy, and the economy’s response to those shocks. Barnichon (2010) documents the increasing volatility of technology shocks relative to demand shocks, while Garin, Pries, and Sims (2018) show that sector-specific shocks have gained importance relative to aggregate economy-wide shocks in the post-1980s U.S. Below I discuss these papers and how the current work differs from them.

Galí and van Rens (2017) is probably the first paper to try to explain the vanishing procyclicality of labour productivity. The key insight of the paper is that a decline in labour market turnover, which reduced hiring frictions, can match the observed decline in labour productivity correlations. With lower cost of employment adjustment, firms use the extensive margin of factor adjustment more than changing the effort margin, thereby bringing down the correlation of labour productivity with output and hours. While the basic idea of falling hiring costs is similar to the current paper, Galí and van Rens (2017) does not pinpoint any particular structural reason as to why the labour market turnover suddenly changed in the mid-1980s. The current paper investigates various structural changes in the labour market as possible candidates for the falling hiring and firing frictions, and finds that de-unionization is the most likely channel. Moreover, the model in Galí and van Rens (2017) predicts that productivity co-moves positively with both output and inputs in response to technology shocks. This is in stark contrast to the empirical finding in the post-War U.S. where labour input is negatively correlated with technology shocks (see for example Galí and Gambetti (2009)). A key element of the model in this paper will be to generate impulse responses to technology and demand shocks that mimic the empirically observed ones.

In the same vein of a mismeasurement story as GR, McGrattan and Prescott (2012) propose that under-estimating the use of intangible capital is the main channel for explaining the vanishing procyclicality of productivity. They argue that if intangible capital is strongly procyclical but it is not included while measuring output, then the measured procyclicality of productivity with value-added will be less. However, they do not present any empirical fact regarding the increased use of intangible capital around the mid-1980s, rather focusing on the Great Recession period of the late 2000s. In fact, I do not find cross-industry evidence that greater investment in intellectual property products (which is the closest measurable proxy for intangible capital) is correlated with larger drop in productivity correlations.

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5 The first version of the paper was available in 2008.
6 The idea of a greater labour market flexibility in the last three decades in the U.S. as an explanation for the vanishing procyclicality of productivity was first discussed in Gordon (2011).
Moving beyond the narrative of mismeasurement in input or output, Barnichon (2010) shows that a large portion of the rise in correlation of labour productivity with unemployment is accounted for by the increasing volatility of technology shocks relative to demand shocks. The main argument is that since technology shocks induce countercyclicality of productivity with labour input and demand shocks induce procyclicality of productivity with labour input, an increasing relative importance of technology shocks will help to explain the fall in unconditional correlations of productivity with hours. However, this explanation is insufficient for two reasons. First, the productivity correlations fell even conditional on a demand shock, whereas conditional on technological shock, the correlation of labour productivity actually increased slightly in the post-1984 period. These changes in the conditional correlations indicate that some form of structural change is required to fully explain the productivity puzzle. Second, the correlation of labour productivity with output conditional on a technology shock has always been positive, and it increased further after the mid-1980s. Hence, increasing importance of technology shocks cannot explain the falling correlation of output with productivity. In fact, Van Zandwegrhe (2010) performs a comparative study of the change in the nature of technology and demand shocks on one hand, and the structural change in the labour market on the other. He concludes that since the productivity correlations have changed conditional on both demand and supply shocks, it is more likely that change in labour market flexibility is the key factor behind the phenomenon.

In contrast to studying demand and supply shocks, Garin, Pries, and Sims (2018) look at changes in the contribution of sector-specific shocks relative to aggregate shock in the total volatility of industrial production, and claim that the increasing importance of sectoral shocks have caused a drop in productivity correlations and also led to jobless recoveries. However, I show in this paper that the empirical finding of increasing importance of sectoral shocks is not robust to the choice of the dataset, and there is reason to doubt that there has been a sudden increase in sectoral reallocation towards more productive sectors since the mid-1980s.

Relating jobless recoveries to the vanishing procyclicality of productivity is also done by Berger (2016), whose model relies on heterogeneity in worker productivity. Crucially, in his model, firms know individual worker productivity and during streamlining and restructuring in a recession they can lay off their least productive workers thereby bringing up the average labour productivity. However, since the focus is only on the recovery part of the business cycle, that model has trouble in generating the full magnitude of the drop in productivity correlations. Moreover, the impulse responses of employment to a TFP shock is positive in Berger’s modified Real Business Cycles model, which goes against the empirical evidence. In the context of jobless recoveries, Panovska (2017) runs a horse race among the different channels of explanations — (i) reallocation of resources across sectors (like in Groshen and Potter (2003), Garin, Pries, and Sims (2018) and others) or occupations (as highlighted by Jaimovich and Siu (2015)); (ii) overhang during booms which leads to restructuring in recessions, like in Berger (2016), (iii) shorter duration of recessions, as pointed out by Bachmann (2012), and (iv) structural changes in the economy, like those highlighted by Gali and Gambetti (2009). Using a VAR analysis, she finds that the most plausible channel explaining jobless recoveries is the one of structural changes.
Therefore, in this paper I will focus exclusively on the structural changes in the economy to explain the productivity puzzle, and see if the same structural changes can also explain jobless recoveries.

The rest of the paper is organized as follows. In Section 2, I document the productivity puzzle, and empirically argue for increased labour market flexibility through de-unionization as the underlying explanation for the puzzle. Section 3 then proposes a dynamic stochastic general equilibrium (DSGE) model featuring key elements of the empirical findings. Section 4 provides calibration of the model parameters and quantifies the performance of the model in matching the changes in business cycle moments observed in the data. Different counterfactual scenarios are also discussed here. Section 5 then discusses the lack of empirical evidence for a host of structural changes that could have potentially explained the productivity puzzle. Finally, Section 6 summarizes key conclusions of the paper.

2 Empirical Evidence

In Section 2.1 I begin by documenting that the cyclical correlations of productivity with both output and labour input have decreased quite abruptly around the mid-1980s in the U.S. After showing that this puzzling finding is robust to different data sources, the choice of de-trending methodology, and even the measure of labour input, I turn to explaining the puzzle in Section 2.2. I investigate the issue in two different ways. First, in Section 2.2.1, I decompose productivity into factor utilization rate and utilization-adjusted productivity, and show that it is really the factor utilization component of measured productivity that has become more countercyclical. Second, in Section 2.2.2, I show that the response of the aggregate U.S. economy to technology and demand shocks have changed around the mid-1980s. Both these findings point towards a structural change in the labour market that made hiring and firing workers suddenly much less costly. In Section 2.3 I show that de-unionization is one structural change in the labour market that is consistent with explaining the fall in employment adjustment cost in the 1980s. Cross-sectional evidence from U.S. states and industries, as well as international evidence from OECD countries point towards decline in union power as a major contributing factor towards higher labour market flexibility that explains the productivity puzzle.

2.1 The productivity puzzle

*Productivity puzzle* refers to the sudden vanishing of procyclicality of productivity around the mid-1980s in the U.S. The existing literature on this puzzle has typically used average labour productivity, defined as output per hour worked, as the measure of productivity. In panels (a) and (b) of Figure 2.1, I corroborate that finding using quarterly data on output and hours worked for the U.S. business sector from 1947 through 2017, sourced from the Labor Productivity and Costs (LPC) dataset of the Bureau of Labor Statistics (BLS). As an alternative measure of productivity, in panels (c) and (d), I use TFP (unadjusted for factor utilization), sourced from Fernald (2014), and find a remarkably similar pattern
of a sudden drop in contemporaneous productivity correlations.\footnote{There is a difference in the levels of the correlations between the two alternative measures of productivity — while TFP has remained procyclical even after the drop, average labour productivity has in fact become countercyclical with hours worked, and acyclical with output. The current paper is not concerned with these level differences, but the sudden drop around the mid-1980s.} While I have used the Baxter and King (1999) bandpass filter to extract the cyclical component of the time-series variables in Figure 2.1, the finding is robust to the choice of the statistical filter.\footnote{For the complete set of robustness checks for the choice of filters, see Panel A of Table A.1 in the Appendix. Using KLEMS data, provided by Jorgenson, Ho, and Samuels (2012), Panel B of the table shows that the drop in labour productivity correlations is also robust to considering annual data for the aggregate U.S. economy. Data for non-farm business sector (not shown here) also produce the same correlation pattern. Findings are also robust to using employment as the measure of labour input instead of total hours worked.}
These changes in productivity correlations have implications for the co-movement of productivity with job flows over the business cycle. One can think of labour input as being composed of an inflow of workers through job creation or vacancies, and an outflow through job separations. Then it is natural to expect that job-creation or vacancy rate should become more countercyclical, and job-destruction or separation rate more procyclical after the 1980s. Using different data sources on job flows, I corroborate these conjectures in Figure 2.2.\(^9\)

From the above findings, it is clear that the puzzle of a sudden vanishing procyclicality of productivity around the mid-1980s in the U.S. is not simply an artefact of a particular dataset, or a specific statistical de-trending process, or the choice of the measure of productivity or labour input. Having established the empirical robustness of the so-called productivity puzzle, I will now consider possible explanations for it.

### 2.2 Explaining the puzzle: Drop in employment adjustment cost

Procyclicality of measured productivity in the U.S. after World War II was traditionally explained through labour hoarding by firms facing costly hiring and firing of workers. So a natural candidate for explaining the vanishing procyclicality of productivity is a fall in employment adjustment cost. However, whether there has indeed been lower factor hoarding after the mid-1980s remains an empirical question. In Section 2.2.1, I study the cyclical properties of factor utilization rate, which is a proxy measure for factor hoarding, and establish that factor hoarding has in fact lost its importance in the post-1980s U.S. In Section 2.2.2, I study the response of the aggregate U.S. economy to technology and demand shocks in a structural VAR set-up. The changes in these responses between the pre and post-1984 periods further confirms the hypothesis that firms have resorted to less labour hoarding in the recent decades.

\(^9\)It is difficult to obtain data on economy-wide job destruction before the late 1970s. However, economy-wide job vacancy rate can be obtained using the monthly Help Wanted Index (HWI) from the Job Openings and Labor Turnover Survey (JOLTS) starting from 1951. Also, for the manufacturing sector, Davis, Faberman, and Haltiwanger (2006) have collected quarterly data on both job creation and destruction rates starting from 1947.
2.2.1 Vanishing procyclicality of factor utilization rate

Commonly used measures of productivity, like labour productivity and TFP, contain an implicit component of factor utilization rate that can itself have cyclical correlations with output and hours. For example, if labour is utilized at a higher rate (by increasing labour effort) during economic booms than during recessions then measured labour productivity will be more procyclical. This can be understood by simply studying a production function with effective labour input, \( Y = A(E.N)^\alpha \), where \( Y \) is the value added, \( E \) is the effort or utilization rate of each worker \( N \), and \( A \) is the utilization-adjusted productivity component. Average labour productivity is defined as \( \frac{Y}{N} = AE^\alpha N^{\alpha-1} \), which is decreasing in \( N \) so long as \( \alpha < 1 \). In an economic downturn, when firms want to reduce the effective labour input, \( E.N \), they face the option of either reducing the number of workers \( N \), or decreasing the utilization rate \( E \). When it is costly to adjust employment, firms mostly change effort. As an extreme example, when \( N \) is fixed over the business cycle due to costly adjustment, all change in labour productivity is explained by changes in effort. Thus, as firms increase \( E \) during booms and decrease it in recessions, labour productivity remains perfectly procyclical. As the cost of adjusting \( N \) falls, firms can now reduce \( N \) in recessions, thereby boosting labour productivity during economic downturns. Thus, a lower hiring and firing cost makes measured productivity less procyclical.

Table 2.1: Reduction in Procyclicality of Factor Utilization Rate

| Variable & Filter Choice | With Output | | With Hours | |
|--------------------------|-------------|-----------------|-------------|
| **Panel A: Quarterly Growth Rate** |
| TFP                      | 0.87        | 0.70            | -0.17       | 0.35        | 0.10            | -0.25       |
| Factor Utilization Rate  | 0.73        | 0.49            | -0.24       | 0.67        | 0.52            | -0.15       |
| Utilization-Adjusted TFP | 0.10        | 0.25            | +0.15       | -0.40       | -0.32           | +0.08       |
| **Panel B: Annual Growth Rate** |
| TFP                      | 0.88        | 0.69            | -0.19       | 0.49        | 0.29            | -0.20       |
| Factor Utilization Rate  | 0.87        | 0.62            | -0.25       | 0.75        | 0.61            | -0.15       |
| Utilization-Adjusted TFP | -0.10       | 0.04            | +0.14       | -0.45       | -0.34           | +0.11       |

*Note:* Data on quarterly and annual growth rates of TFP, factor utilization rate, utilization-adjusted TFP, output and hours worked for the U.S. business sector are sourced from Fernald (2014). Since Fernald (2014) only provides the growth rates of the three variables, robustness to other de-trending methods cannot be established.

This argument of procyclical labour utilization was used to justify the procyclicality of TFP in post-war U.S. economy. However, it remains to be established whether the drop in cyclical productivity correlations was driven by less factor hoarding or more countercyclical utilization-adjusted productivity. Using hours per worker as a proxy that is proportional to unobserved changes in both labour effort and capital utilization, Basu, Fernald, and Kimball (2001) generated a composite factor utilization rate series and a utilization-adjusted TFP series. Studying the cyclical property of those series in Table 2.1, one can safely conclude that the drop in cyclical correlations of measured productivity is driven by the factor utilization component of TFP, and not the ‘true’ productivity...
component. As discussed above, factor utilization can become less procyclical if factor adjustment along the extensive margin over the business cycle becomes more pervasive in comparison to changes in unobserved labour effort and work-week of capital.

Notwithstanding the fall in procyclicality of factor utilization rate, utilization-adjusted TFP has historically been and continues to be much less procyclical than factor utilization. Hence, purely in a mechanical variance decomposition sense, if the relative contribution of factor utilization rate falls in the total variability of aggregate TFP, measured productivity will become more countercyclical. In fact, Table 2.2 shows that the share of total variation of TFP that is explained by the more procyclical component of factor utilization rate has diminished sharply in the post-1984 period. Such shift towards a greater relative importance of the extensive margin of factor adjustment can emanate from a drop in the cost of hiring and firing of factors, particularly labour.

<table>
<thead>
<tr>
<th>Variable &amp; Filter Choice</th>
<th>Variances</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1948-1983</td>
</tr>
<tr>
<td><strong>Panel A: Quarterly Growth Rate</strong></td>
<td></td>
</tr>
<tr>
<td>Total Factor Productivity (TFP)</td>
<td>17.55 (100%)</td>
</tr>
<tr>
<td>Factor Utilization Rate</td>
<td>11.67 (66.5%)</td>
</tr>
<tr>
<td>Utilization-Adjusted TFP</td>
<td>5.88 (33.5%)</td>
</tr>
<tr>
<td><strong>Panel B: Annual Growth Rate</strong></td>
<td></td>
</tr>
<tr>
<td>Total Factor Productivity (TFP)</td>
<td>4.56 (100%)</td>
</tr>
<tr>
<td>Factor Utilization Rate</td>
<td>3.79 (83.1%)</td>
</tr>
<tr>
<td>Utilization-Adjusted TFP</td>
<td>0.77 (16.9%)</td>
</tr>
</tbody>
</table>

Note: Data on quarterly and annual growth rates of TFP, factor utilization rate and utilization-adjusted TFP are sourced from Fernald (2014). Since Fernald (2014) only provides the growth rates of the three variables, robustness to other detrending methods cannot be established. Percentages in parentheses refer to the share of total variance of TFP that is explained by each component. While calculating the variance of the components, the covariance term was equally split, e.g., \( \text{Var (Factor Utilization Rate)} + \text{Cov (Factor Utilization Rate, Utilization-Adjusted TFP)} \) is taken to be the variance of factor utilization rate, and \( \text{Var (Utilization-Adjusted TFP)} + \text{Cov (Factor Utilization Rate, Utilization-Adjusted TFP)} \) is taken to be the variance of utilization-adjusted TFP.

Falling employment adjustment cost should in turn imply a rise in the volatility of employment relative to those of output and factor utilization. Figures 2.3a and 2.3b show the dramatic rise in the volatility of hours and employment relative to that of output exactly at the time of the sudden drop in the productivity correlations. Finally, Figure 2.3c shows how the relative importance of employment (the extensive margin of labour adjustment) vis-à-vis the intensive margin of factor utilization has progressively increased from around the same time. This rise in the relative volatilities of measured labour inputs happened immediately after the onset of the so-called Great Moderation, when the absolute volatilities of output and labour input fell precipitously in the late 1970s. As is evident from Figure A.1, even though the volatilities of output, hours and employment follow a similar time trend, the magnitude of reduction in volatility is larger for output than for the labour inputs. This leads to the eventual increase in the volatility of labour input relative to that of output.
Figure 2.3: Relative Volatility of Hours & Employment over the Business Cycle (1954-2010)

Note: Data for hours, employment and output is sourced from the BLS-LPC quarterly dataset for the U.S. business sector. Factor utilization data (in quarterly growth rates) is taken from Fernald (2014). The Christiano and Fitzgerald (2003) bandpass filter between 6 and 32 quarters have been used to extract the cyclical component of the variables in panels (a) and (b), while the annualized quarterly growth rate has been used in panel (c). A centred rolling window of 15 years is used to calculate the second moments. Findings are robust to alternative choice of filters and window-sizes.

To summarize, the vanishing procyclicality and reduced volatility of factor utilization over the business cycle, induced by a drop in employment adjustment cost, can not only explain the fall in measured productivity correlations but also the rise in relative volatility of employment.

2.2.2 Changes in response to technology and demand shocks

Structural changes in the labour market that make hiring and firing of workers easier for firms should have implications for how the economy responds to different types of shocks. In this section, I focus on such changes in the response of the aggregate U.S. economy to technology and demand shocks between the pre and post-1984 periods. I perform a time-varying structural vector auto-regression (SVAR) with labour productivity growth and per capita hours, as in Galí and Gambetti (2009). There are two main advantages of this specification: first, it allows one to control for low-frequency movements in per capita hours without having to extract the cyclical component of hours through any form of ad hoc time series filtering, and second, it allows one to know the complete dynamics of the impulse responses over the years so that it can be pin-pointed as to exactly when the responses began to change. Since the current paper focusses on documenting the changes in the impulse responses during the mid-1980s, this method of time-varying SVAR is the most suitable for the purpose. For a detailed discussion on the choice of SVAR specification, refer to Appendix A.6.

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10Chang and Hong (2006) criticize the use of labour productivity as the measure of productivity. They argue that using labour productivity instead of TFP mislabels changes in input mix (i.e., permanent changes in capital-labour ratio) as technology shocks. Hence, as a robustness check, I perform the same SVAR replacing labour productivity with TFP.

11In Figures A.9 and A.11, I show the dynamics of the impulse responses by year. This confirms the choice of 1984 as the approximate year of the structural change, although no rigorous structural change test was performed.
Figure 2.4: Impulse Responses to Technology & Demand Shocks

Note: Impulse Response Functions (IRF’s) of per-capita hours, per-capita output and average labour productivity from a 2-variable (viz., labour productivity growth and per-capita hours) time-varying long-run SVAR. IRF’s for the pre-1984 period (1956-1983) are in blue, and the post-1984 (1984-2017) IRF’s are in red dashed lines. Data is sourced from the Labor Productivity and Costs (LPC) quarterly dataset for the U.S. business sector, published by the Bureau of Labor Statistics (BLS).
Response to technology shock

Panels (a), (c) and (e) of Figure 2.4 respectively show the impulse responses of per capita hours, per capita output and labour productivity to a positive technology shock separately for the pre-1983 (solid blue lines) and post-1984 (dashed red lines) periods. Of these the only statistically significant difference between the two sub-periods is the change in the impulse response of hours, as shown in Appendix Figure A.10. While I find that per capita hours worked respond negatively on impact to a positive technology shock throughout the post-War era, the negative response is much less intense and barely different from zero in the post-1984 period.\(^\text{12}\) A common explanation provided for the diminished response of hours to technology shocks is that the monetary policy conducted by the Federal Reserve became more accommodative of technology shocks to the economy. But what is most relevant in the context of the productivity puzzle is that the muted negative response of hours to a positive technology shock increases the productivity correlation with labour input. This acts as a counterforce to the vanishing procyclicality of productivity.

\[\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2_5.png}
\caption{Conditional Correlations of Productivity with Hours}
\textit{Note:} Time-varying correlations of per capita hours with (a) labour productivity growth, and (b) TFP growth, conditional on technology shock (blue dashed line) and demand shock (red dotted line).
\end{figure}\]

Response to demand shock

In response to a positive demand shock, hours increased by roughly the same amount in the pre- and post-1984 periods, while the positive response of output on impact was drastically muted after the mid-1980s. Since average labour productivity is nothing but output per hour worked, the reduced response of output and a near-identical response of hours imply a muted response of labour productivity to

\(^{12}\)Contrary to my findings, Gali and Gambetti (2009) did not find a starkly muted response of hours conditional on a technology shock in the post-1984 period. This difference emanates from extending the post-1984 period with more recent years of data — while they used data till 2005, my dataset extends till fourth quarter of 2017. When TFP is used as the measure of productivity instead of labour productivity, a similar difference between the two sub-periods in the initial response of hours emerges (see Figures A.12a and A.13a).
a demand shock. A qualitatively similar result is obtained when estimating the SVAR with TFP growth instead of labour productivity growth. While the impulse response of TFP remains positive albeit the reduction in magnitude (see Figure A.12d), the on-impact response of labour productivity turns negative after 1984 (see Figure 2.4f). The muted response of productivity and an unchanged response of hours to a demand shock imply that conditional on a demand shock, the correlation of productivity with hours must drop in the post-1984 era. This is shown in Figure 2.5.

The reduction in productivity correlation conditional on a demand shock proves that it is not the case of changing composition of shocks to the U.S. economy that have induced the sudden fall in unconditional productivity correlation, rather there must have been deeper structural changes in the economy that caused firms to change output by a smaller magnitude when hit with the same demand shock. An example of such a structural change is the decline in the labour adjustment cost. Given a positive demand shock, when employment adjustment is less costly, a firm does not increase the intensive margin of effort as much, which causes output and productivity to not rise as much for a given increase in employment and hours worked. This decreases the correlation of productivity with measured labour input.

In summary, while the change in response to demand shocks predicts decreasing procyclicality of productivity, the change in response to technology shocks predicts just the opposite. How all these opposing forces of the changing nature of technology and demand shocks combine to generate the change in the unconditional correlation of productivity with output and hours will be a crucial element of the modelling exercise in paper.

2.3 De-unionization: Why did employment adjustment cost drop?

The reduced importance of factor utilization rate in measured productivity and the change in productivity correlation conditional on technology and demand shocks establish that higher dependence on hiring and firing of workers instead of the intensive margin of effort adjustment has caused the procyclicality of productivity to fall so drastically. However, what observable structural change in the labour market can bring about such a sudden drop in employment adjustment cost remains an open question so far.

A fall in the cost of hiring and firing of workers can be brought about by a host of structural changes that increase labour market flexibility, e.g., relaxing employment protection regulations, quicker matching between workers and jobs through online job-search platforms, increasing the share of part-time and/or temporary workers, and the decline of union power. An empirically identifiable labour market change that occurred in the U.S. almost around the same time as the change in the productivity correlations is the decrease in size and influence of labour unions. In Figure 2.6 we see

\footnote{For statistical significance of the differences in the impulse responses between the two sub-periods, refer to panels (b), (d) and (f) of Figure A.10.}

\footnote{This is not to claim that de-unionization is the only explanatory factor for falling employment adjustment cost. See Appendix A.2 for discussion on the other plausible channels of increased labour market flexibility. Acknowledging the possibility of multiple underlying reasons behind increased labour market flexibility, the theoretical model in this paper}
that union membership among working individuals (both in terms of rates and absolute numbers) was rising in the U.S. until the early 1970s, after which it remained flat for a decade (with falling rates for the private industries and increasing rates for the public sector), and started falling sharply since the early 1980s. To emphasize how dramatic the de-unionization event around the 1980s was, one can compare the growth rates in union density for 30 years before and after 1980. In the three decades preceding 1980, unionization rate remained almost constant, while between 1980 and 2010 it fell by roughly 50% in aggregate and by 67% in the private sector.

![Figure 2.6: Density & Membership Size of Labour Unions in the U.S. (1930-2014)](#)

**Note:** Figures represent the number and percentage of non-agricultural wage and salary employees who are union members. Data before 1977 is sourced from Historical Tables published by the Bureau of Labor Statistics. Data between 1977 and 1981 comes from May earnings files, and from 1983 onwards it comes from the Outgoing Rotation Group (ORG) earnings files of the Current Population Survey (CPS), collected by Hirsch and Macpherson (2003). Union coverage rates are slightly different from union membership rates but follow a similar time-trend.

Farber and Western (2002) argue that this stark reversal of unionization trend in the U.S. was precipitated by a fall in the annual number of union elections — a key channel of recruiting new union members. In fact, the unfavourable political climate was strengthened by President Reagan’s strong stand against the air-traffic controllers’ strike of 1981, and the much-publicized appointment of the Reagan Labor Board in 1983. On the other hand, Acemoglu, Aghion, and Violante (2001) and Dinler-soz and Greenwood (2016) argue that skill-biased technological change can explain de-unionization in the U.S., while Açikgöz and Kaymak (2014) show that roughly 40% of the drop in unionization rates in the U.S. can be explained by the rise in skill premium in wages. Foll and Hartmann (2019) argues will be agnostic about the exact source of the fall in labour adjustment cost along the extensive margin. In contrast, Zanetti (2007) shows that a standard New Keynesian monetary model with unionized labour market can explain European business cycle data much better than one with a competitive labour market.

15The number of elections held fell by almost 50%, from about 8000 in 1980 to about 4400 in 1990, with most of this drop happening sharply between 1980 and 1985.
that routine task-biased technical change is not only the driving force behind job market polarization, but also de-unionization. However, since skill-biased or routine-biased technological change happened in most developed economies, the sudden trend reversal in union density in the U.S. is likely to be mostly driven by political factors. A change in the political climate regarding labour unions can also mean that changes in union density might be an underestimate of the change in the real bargaining power of unions. While it is difficult to directly measure the power of unions, one good proxy is to look at the number of work stoppages, which are usually organized by unions. From Figure 2.7, one can see that large-scale work stoppages dropped by almost 90% of its pre-1980 level quite suddenly within a matter of couple years. Thus, although decline in union membership from the early 1980s was a somewhat gradual process which might seem inconsistent as an explanation for the strikingly rapid decline in the productivity correlations, union power seems to have declined more promptly.

![Figure 2.7: Number of Work Stoppages involving 1000 or more workers in the U.S. (1947-2017)](image)

**Note:** Data is sourced from the Economic News Release of the Bureau of Labor Statistics (BLS).

One concern about de-unionization being the main driving force behind falling procyclicality of productivity is that union rates were already quite low in the U.S. even before 1980, roughly 20% of the workforce, and so falling union rate should not matter much. Taschereau-Dumouchel (2017) argues that it is not so much the fraction of union-jobs but the presence of political threat of unionization that matters for labour market outcomes. In that sense, a change in the political atmosphere can be crucial for de-unionization to matter. In fact, Riddell (1993) documents how this drop in unionization is conspicuously absent in Canada. It should be noted as anecdotal evidence that Canada, which did not experience a similar de-unionization, also did not undergo a drop in cyclical correlations of productivity. On the other hand, United Kingdom, experienced both de-unionization and drop in productivity correlations with output and hours. This evidence is consistent in spirit with Gnocchi and Pappa (2009) who find that union coverage is one labour market rigidity that most significantly affects business cycle statistics in a sample of 20 OECD countries.16

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16For further details on international evidence for de-unionization as an explanation for vanishing procyclicality of labour productivity, see Appendix A.3.
Cross-sectional evidence from U.S. states and industries

Having established that, in the aggregate U.S. economy, de-unionization since the early 1980s is consistent, in terms of timing, with falling procyclicality of labour productivity, and rising volatility of employment relative to that of output and factor utilization, I now use sectoral variation across U.S. states and industries to see if a larger magnitude of de-unionization is indeed correlated with a greater reduction in labour productivity correlation. In particular, I run the following cross-sectional regression:

$$\Delta \text{Corr} (lp_i, h_i) = \alpha + \beta \Delta \ln (\text{Union Density})_i + \varepsilon_i,$$

(2.1)

where $lp_i$ and $h_i$ are the cyclical components of labour productivity and hours in industry or state $i$.\(^{17}\)

Figure 2.8: Cross-Industry Evidence for De-unionization

Note: Data on industry-level unionization rates comes from the Current Population Survey (CPS), collected by Hirsch and Macpherson (2003). Labour productivity is defined as real value added per hour worked. Annual industry-level data on value-added, hours and employment between 1947 and 2010 comes from KLEMS dataset, collected by Jorgenson, Ho, and Samuels (2012). CPS industry codes for unionization and SIC industry codes in KLEMS were matched to create a consistent set of 17 U.S. industries. The Baxter and King (1999) bandpass filter between 2 and 8 years have been used to de-trend the variables. Since industry-level union data is available only from 1983 onwards, and the CPS industry codes change from 1992, to minimize concordance error I have used the change between 1983 and 1991 as the measure of change in union density. Size of the bubbles represent average industry employment level. The p-value of the slope coefficient using robust standard error is reported in parentheses.

Figures 2.8 and 2.9 show a significant positive relation between the degree of de-unionization and the magnitude of the drop in productivity correlations across 17 U.S. industries and 51 U.S. states respectively. In order to avoid the result being driven by small industries or states, I weight the observations with the average employment level in each industry or state.

One concern while using cross-sectional variation in de-unionization in the above regression is

\(^{17}\)I do not have data with simultaneous variation across states and industries, and so a single regression exploiting that industry $\times$ state variation could not be performed.
that union densities might not have fallen substantially within individual industries or states. In other words, the fall in aggregate unionization rate might have been driven by employment shifts towards less unionized sectors and regions, rather than de-unionization within them. This would be problematic for identifying the slope coefficient in regression (2.1), because of lower cross-sectional variation in changes in union densities. However, a simple within-between decomposition\(^\text{18}\) of aggregate de-unionization shows that nearly 88% of the fall in aggregate union density happened within the 17 industries considered here between 1983 and 1991. Similarly, 91% of the total fall in the unionization rates in the U.S. between the pre- and post-1984 periods took place within the states, and not through employment shifts towards less unionized states.

![Figure 2.9: Cross-State Evidence for De-unionization](image)

**Note:** Data on state-level unionization rates comes from the *Current Population Survey* (CPS), collected by Hirsch and Macpherson (2003). State-level data on real non-farm gross domestic product and total employment between 1969 and 2010 is sourced from the *Bureau of Economic Analysis* (BEA). Since hours worked data is not available at the state level, employment is used as the measure of labour input and labour productivity is defined as the state real non-farm gross domestic product per worker. I use annual growth rate as the filter because the preferred Baxter and King (1999) filter leads to 12 years of missing observations and leaves only 3 years of data before 1984. All changes in variables are calculated as the difference between the pre and post-1984 averages. Although observation for each state is weighted by its average employment in the regression, to improve readability I have not shown the weights here through bubbles, rather made it explicit in Figures A.3 and A.4 in Appendix A.4. The p-value of the slope coefficient using robust standard error is reported in parentheses.

For the state-level regression, there is an additional concern that in recent years many U.S. states have adopted Right-to-Work legislations promoting their “pro-business” outlook, thereby rendering the labour unions a lot less powerful in those states. In that case, a decline in union density in these Right-to-Work states should barely matter for explaining the drop in productivity correlations. In

\(^{18}\)Total change in union density, \(\Delta u = \text{Within-}i \text{ change, } \sum_{i=1}^{17} \bar{e}_i \Delta u_i + \text{Between-}i \text{ change, } \sum_{i=1}^{17} \bar{u}_i \Delta e_i\), where \(\bar{e}_i\) is the average employment share and \(\bar{u}_i\) is the average union density in industry or state \(i\).
Appendix Figure A.5, I show this is indeed the case, with only the so-called non-Right-to-Work states driving the positive relationship between de-unionization and drop in productivity correlation.

One alternative identification strategy to the one considered above, is to perform a difference-in-difference estimation à la Card (1992). In that strategy one assumes that the intensity of the de-unionization event is larger in industries where a larger fraction of the workers was unionized to begin with. Thus, instead of regressing the change in the productivity correlation on the change in the union density, one simply regresses it on the pre-1984 level of union density. This method of identification also corroborates my finding that union density had a role to play in the vanishing procyclicality of labour productivity.19

Figure 2.10: Relative Volatility of Employment & Change in Labour Productivity Correlation

Note: Data is for 31 U.S. industries from the annual KLEMS dataset, collected by Jorgenson, Ho, and Samuels (2012). The change in the second moments is the difference between their values in the post-1984 period (1984-2008) and the pre-1984 period (1959-1983). Regressions are weighted by the time-average of industry-level employment, depicted by the size of the bubbles. The p-value of the estimated slope using robust standard error is reported in parentheses. The Baxter and King (1999) bandpass filter between 2 and 8 years has been used to extract the cyclical component of the variables. Findings are robust to using other filters.

The above cross-sectional evidence supports my claim that de-unionization is positively correlated with vanishing procyclicality of labour productivity, but it is still left to show that industries with a greater fall in productivity correlation experienced a larger increase in the volatility of employment (that is, the extensive margin of labour adjustment) relative to that of output and utilization (that is, the intensive margin of factor adjustment). Since utilization data is not available at the industry level, I use hours per worker as a proxy for the measure of intensive margin of labour adjustment. From Figure 2.10 one can clearly find a statistically significant negative relation between the change in labour productivity correlation on one hand and the relative volatility of employment on the other, across U.S. industries.

The negative correlation patterns in Panels (a) and (b) of Figure 2.10 are similar, but there is a subtle difference between the two scatter plots. A lot of the industries experienced a rise in the

19For details on the difference-in-difference strategy and the results based on that, refer to Appendix A.5.
relative volatility of employment with respect to output, while very few experienced a similar rise in volatility of employment relative to that of hours per worker. This finding that the extensive margin of employment adjustment became less volatile relative to the intensive margin of changing hours per worker in almost all industries is an apparent aberration from what one would expect under falling employment adjustment cost. This is particularly puzzling in light of the evidence in Figure 2.3c that employment became increasingly more volatile relative to factor utilization since the 1980s. To understand why the dynamics of hours per worker and factor utilization might vary, it is instructive to study the industry-level differences in the elasticity of output with respect to hours per worker. Basu, Fernald, and Kimball (2001) find that the responsiveness of output to hours per worker is vastly different across industry-groups, e.g., the non-durables manufacturing sector is roughly 60% more responsive than the durables manufacturing industries, and more than 3 times as responsive as the service sector. The declining share of manufacturing in the U.S. can therefore explain the larger decline in volatility of factor utilization at the aggregate level than within individual industries.

**Summary of empirical findings**

I have shown so far that a sudden and significant drop in the cyclical correlations of measured productivity with output and hours during the mid-1980s in the U.S. was driven by the vanishing procyclinality of factor utilization, and not by changes in the cyclical correlations of ‘true’ productivity. The cause for less procyclical factor utilization was pinned down to a lower cost of employment adjustment due to rapid de-unionization during the early 1980s. The rise in labour market flexibility can also explain the rise in volatility of employment relative to both value-added and factor utilization volatility. This mechanism of structural changes in labour market institutions was also shown to be consistent with the substantial changes in the response of the U.S. economy to technology and demand shocks.

The challenge of the theoretical model in the next section will not only be to explain the observed fall in productivity correlations and the rise in the relative volatility of employment due to more labour market flexibility, but also to make explicit the relative quantitative importance of various contemporaneous structural changes (e.g., more accommodative monetary policy, reduced shock volatility in Great Moderation, lower hiring cost and higher bargaining power for firms due to de-unionization, etc.) in explaining the productivity puzzle.

**3 Model**

I will consider a standard New Keynesian model with two exogenous shocks — a technology shock to firm productivity, and a monetary policy shock to the nominal interest rate. I will deviate from the textbook model in two directions — first, I will explicitly consider both extensive and intensive margins of labour input adjustment (namely, employment and effort), and second, I will consider the presence of

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20 The post-1984 change in the volatility of employment relative to that of hours per worker is not very robust to the choice of different datasets and time-series filters (see Table A.3 in Appendix). Regardless of the filter used, the volatility of employment relative to hours per worker did not show any stark upward trend after the mid-1980s.
a convex cost of employment adjustment for firms. Crucially, the absence of adjustment cost along the intensive margin of effort variation will lead firms to depend more on effort adjustment when hiring costs are high. This drives the main result of vanishing procyclicality of effort, and consequently measured labour productivity, in the post-1984 era when hiring costs decreased significantly.

3.1 Households

I assume a large number of infinitely lived identical households in the economy, with each household having a continuum of identical members represented by the unit interval. The household is the relevant decision unit for consumption and labour supply choices, and full consumption risk sharing is assumed within each household. Households seek to maximize the present value of lifetime expected utility, discounted at rate $\beta \in (0, 1)$,

$$
\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[ \ln C_t - \chi L_t \right]
$$

subject to the per-period budget constraint,

$$
\int_0^1 P_i^t C_{it} di + Q_t D_t \leq \int_0^1 W_{jt} N_{jt} dj + D_{t-1} + \Pi_t.
$$

Here, $P_i^t$ and $C_{it}$ are the price and consumption of final good $i$, $W_{jt}$ is the nominal wage paid at firm $j$, $D_t$ denotes the amount of one-period bonds purchased at price $Q_t$, and $\Pi_t$ represents any lump-sum income including dividends from ownership of firms and government taxes and transfers. Household’s aggregate consumption bundle, $C_t \equiv \left( \int_0^1 C_{it}^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}}$ is an index of the quantities consumed of different types $i$ of final goods, and is priced at $P_t \equiv \left( \int_0^1 P_{it}^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}}$, with $\varepsilon > 1$ being the Kimball aggregation parameter for the unit mass of final goods. The second term in the period utility function represents disutility from effective labour supply $L_t$, which not only depends on the fraction $N_t$ of household members who are employed but also the amount of effort, $E_t$ exerted by each employed member. More specifically, I assume the following functional form for effective labour supply, $L_t \equiv \frac{1+\zeta E_{it}^{1+\phi}}{1+\zeta} N_t$. The parameter $\chi > 0$ measures the importance of disutility from forgone leisure, while $\zeta \geq 0$ measures the importance of effort in that disutility from working. The elasticity parameter $\phi \geq 0$ measures the degree of increasing marginal disutility from exerting more effort.

I make the simplifying assumption of a constant hours per worker so that the only source of intensive margin adjustment in labour supply is effort. More importantly, I assume that households take into account the endogenous impact of employment adjustment decisions on the level of effort exerted by each of its members.

Consumption maximization for any given level of expenditure, $P_tC_t$ is done by choosing the optimal amount of consumption of each intermediate good, and the resulting demand function for good $i \in [0, 1]$ is given by

$$
C_{it} = \left( \frac{P_{it}}{P_t} \right)^{-\varepsilon} C_t
$$

(3.1)
The intertemporal optimality condition is given by

\[ Q_t = \mathbb{E}_t \left( \frac{P_t}{P_{t+1}} \Lambda_{t,t+1} \right) \]  

where \( \Lambda_{t,t+k} = \beta^k \frac{C_t}{C_{t+k}} \) \( \forall t, k \) is the stochastic discount factor measuring the marginal rate of intertemporal substitution.

### 3.2 Firms

I model the production side of the economy as a two-sector structure — final and intermediate goods sectors. Households supply labour only to firms in the intermediate goods sector who produce a variety of intermediate goods in a perfectly competitive set-up. Final goods firms do not employ labour, and effectively only re-package the intermediate goods and sell them in the market at a mark-up over marginal cost, subject to restrictions in the frequency of their price-setting decisions.

#### 3.2.1 Final goods

A continuum of monopolistically competitive firms constitutes the final goods market, with each firm \( i \in [0,1] \) producing a differentiated final good \( Y_{it} \) according to the production function, \( Y_{it} = X_{it} \), where \( X_{it} \) is the quantity of the single intermediate good used by the final good firm \( i \) as an input. In the absence of nominal rigidities, profit maximization leads to the following price-setting condition for all \( t \),

\[ P_{it} = \left( \frac{\varepsilon}{\varepsilon - 1} \right) P^I_t \]  

where \( P^I_t \) is the price of the intermediate good, and the factor \( \left( \frac{\varepsilon}{\varepsilon - 1} \right) \) is the optimal mark-up over the marginal cost of production. However, à la Calvo (1983), I assume that final goods firms are precluded from setting their prices optimally in any period with probability \( \theta_p \in [0,1] \). This probability is independent both across firms, and of the time elapsed since the last nominal adjustment. This ensures that the fraction of firms changing their prices in any given period is a constant \( (1 - \theta_p) \), which can be interpreted as the degree of nominal flexibility in the economy. Thus, the law of motion for the aggregate price level in the economy, \( P_t \) becomes a weighted average of the optimally chosen price, \( P^*_t \) and the price that prevailed in the last period, \( P_{t-1} \), with the weight being the probability of nominal adjustment:

\[ p_t = \theta_p p_{t-1} + (1 - \theta_p) P^*_t \]  

where the lower case letters denote the natural logarithms of the corresponding upper case variables. Since all firms face an identical problem every period, the optimal price, \( P^*_t \) is the same across firms, and is given by

\[ P^*_t = \mu^p + (1 - \beta \theta_p) \sum_{k=0}^{\infty} (\beta \theta_p)^k \mathbb{E}_t \left( P^I_{t+k} \right) \]  

22
where \( \mu^p \equiv \ln \left( \frac{e^t}{e^{t-1}} \right) \). Combining equations (3.4) and (3.5), one can derive the inflation equation as follows:

\[
\pi_t^p = \beta E_t (\pi_{t+1}^p) - \lambda_p \mu_t^p
\]  

(3.6)

where \( \pi_t^p \equiv p_t - p_{t-1} \) is price inflation, \( \lambda_p \equiv \frac{(1-\theta_p)(1-\beta_p)}{\theta_p} \) and \( \mu_t^p \equiv \mu_t^p - \mu^p = p_t - p_t^l - \mu^p \) is the deviation in logs of the average mark-up from its steady state value.\(^{21}\)

### 3.2.2 Intermediate goods

Each intermediate goods firm \( j \in [0, 1] \) faces the production function \( Y_{jt}^I = A_t E_{jt}^N N_{jt} \), where \( A_t \) is the technology term common across all firms, and the parameter \( \psi > 0 \) measures the additional returns to effort over employment.\(^{22}\) Clearly, this parameterization of the production function assumes short run increasing returns to effective labour, which is a standard feature of models trying to generate procyclical movements of labour productivity in response to a demand shock.\(^{23}\) The productivity term \( A_t \) has the following exogenous stochastic process: \( a_t \equiv \ln (A_t) = \rho_a a_{t-1} + \varepsilon_t^a \), where \( \varepsilon_t^a \) is a white noise process with variance \( \sigma_{\varepsilon_a}^2 \). Since the production function explicitly includes the factor utilization term, namely, effort \( E_{jt} \), the productivity term \( A_t \) should be interpreted as the utilization-adjusted TFP.

Workers get separated from their jobs at intermediate goods firms at the exogenous gross rate of \( \delta \in (0, 1) \), but every period \( t \) firm \( j \) hires back new workers \( H_{jt} \), subject to a per-worker adjustment cost function, \( G_t = \Gamma H_t^\gamma \), with the parameters \( \Gamma \) and \( \gamma \) being strictly positive, and \( H_t \equiv \int_0^1 H_{jt} dj \) denoting aggregate level of hiring.\(^{24}\) This implies that employment at firm \( j \) has the following law of motion

\[
N_{jt} = (1 - \delta) N_{jt-1} + H_{jt}
\]

(3.7)

Because of the presence of labour market frictions in the form of a hiring cost, wages and employment may differ across firms, since they cannot be instantaneously arbitraged out by free movement of workers from low to high wage firms. Therefore, in what follows, the subscript \( j \) on wages and employment will signify this potential difference across firms. Faced with the common hiring cost

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\(^{21}\)See Galí (2008) for derivation of equations (3.5) and (3.6).

\(^{22}\)One might be concerned that whatever is being labelled as ‘effort’ in the production function is in fact capital, the missing factor of production. In Appendix A.8, I contrast the cyclical properties of capital with that of factor utilization (which is a proxy for ‘effort’) and show how they evolved differently. This allays the identification concern of ‘effort’ being equivalent to capital. Additionally, the production function considered here can be thought as a special case of a standard Cobb-Douglas production function with effective labour and capital, \( Y_{jt} = A_t (E_{jt} N_{jt})^{\psi} K_{jt}^{1-\psi} \), provided capital per worker, \( K_{jt} / N_{jt} \), is held constant over the business cycle.

\(^{23}\)Gordon (1993) emphasizes the theoretical need for the presence of such increasing returns to labour for explaining business cycle facts. Empirical works by Basu (1996), Basu, Fernald, and Kimball (2001) and others have confirmed increasing returns to scale production functions, both for durable manufacturing and services industries.

\(^{24}\)The motivation for this hiring cost is best summarized in Heckman, Pagés-Serra, Edwards, and Guidotti (2000): “...in the face of a positive shock firms may want to hire additional workers, but they will take into account that some workers may have to be fired in the future if demand turns down. This prospective cost acts as a hiring cost...” Moreover, more powerful unions can make this hiring cost to rise for firms. This link between union density and hiring cost will be crucial for the calibration of the model.
function, \( G_t \) and given the nominal wage \( W_{jt} \), firm \( j \)'s optimal hiring policy is given by the condition,

\[
MRPN_{jt} = \frac{W_{jt}}{P_t} + G_t - (1 - \delta) \mathbb{E}_t (\Lambda_{t+1} G_{t+1}) \tag{3.8}
\]

where \( MRPN_{jt} = \frac{P_t Y^j_t}{N^j_t} \) is the marginal revenue product of employment expressed in terms of final goods. This condition implies that each period the firm hires workers up to the point where the marginal revenue from an additional employment equals the cost of that marginal worker, where the cost involves not only the wage and the hiring cost in the current period, but also the discounted future savings from having to hire \((1 - \delta)\) fewer workers in the following period. Solving equation (3.8) forward, one has the following expression for the average hiring cost,

\[
G_t = \mathbb{E}_t \left[ \sum_{k=0}^{\infty} \Lambda_{t+k} (1 - \delta)^k \left( MRPN_{jt+k} - \frac{W_{jt}}{P_{t+k}} \right) \right] \tag{3.9}
\]

For notational convenience in deriving the log-linearized version of equation (3.8) later on, I define the net hiring cost as \( B_t \equiv G_t - (1 - \delta) \mathbb{E}_t (\Lambda_{t+1} G_{t+1}) \), such that equation (3.8) can be re-written as

\[
MRPN_{jt} = \frac{W_{jt}}{P_t} + B_t \tag{3.10}
\]

### 3.3 Labour market

I assume wages are negotiated and potentially adjusted every period through a Nash bargaining process between the intermediate goods firms and the households to split the total surplus generated from an established employment relation. The surplus accruing to the firm \( j \) and the household members who work at firm \( j \) are given by the following two equations respectively,

\[
S^F_{jt} = MRPN_{jt} - \frac{W_{jt}}{P_t} + (1 - \delta) \mathbb{E}_t (\Lambda_{t+1} S^F_{jt+1}) \tag{3.11}
\]

\[
S^H_{jt} = \frac{W_{jt}}{P_t} - MRS_{jt} + (1 - \delta) \mathbb{E}_t (\Lambda_{t+1} S^H_{jt+1}) \tag{3.12}
\]

where \( MRS_{jt} = \frac{\chi C_t}{1+\xi} + \Psi_H P_t K_t Y^j_t \) is the household’s marginal rate of substitution between consumption and employment at firm \( j \), or equivalently the marginal disutility of employment expressed in terms of the final goods bundle. The non-zero term \( \Psi_H \equiv \frac{\psi}{1+\phi} \left( 1 - \frac{(1+\phi) W_{jt} N^j_t}{(1+\phi-\psi) P_t C_t} \right) \) arises due to the endogenous response of effort to changes in employment. It is interesting to note that profit maximization by firms implies that the firm surplus \( S^F_{jt} \) equals the per worker hiring cost, \( G_t \). The average hiring cost can thus be interpreted as what the firm potentially saves from maintaining an existing employment relation.

Denoting the relative bargaining power of firms vis-à-vis workers by the parameter \( \xi \in (0,1) \), the Nash bargaining set-up solves the following problem
max_{W_{jt}} \left( S_{jt}^F \right)^{\xi} \left( S_{jt}^H \right)^{1-\xi}

subject to equations (3.11) and (3.12). The solution to the above bargaining problem implies a constant share rule, \( \xi S_{jt}^H = (1-\xi) S_{jt}^F \), which translates to the equilibrium wage condition, \( \frac{W_{jt}}{P_t} = \xi MRS_{jt} + (1-\xi) MRPN_{jt} \). Substituting for \( MRPN_{jt} \) and \( MRS_{jt} \) in the above wage equation, one can write the average Nash-bargained wage (upto a first order approximation) as

\[
W_t = \xi MRS_t + (1-\xi) MRPN_t
\]

So far, I have assumed that firms can re-negotiate wages every period. However, this militates against the empirical evidence of substantial nominal wage rigidities, e.g., the average frequency of wage changes is often found to be more than one year. Incorporating Calvo-type nominal wage stickiness is quite straightforward and does not alter the main intuition of the wage-setting process discussed here. In particular, I assume \( \theta_w \) fraction of firms cannot re-optimize their nominal wages in each period, thereby leading to the law of motion for average nominal wage, \( w_t \equiv \int_0^1 w_{jt}dj \) as \( w_t = \theta_w w_{t-1} + (1-\theta_w) w^*_t \). In this set-up, the deviation between the actual average real wage \( (\omega_t \equiv w_t - p_t) \) and the average Nash-bargained wage under a counterfactual flexible wage environment \( (\omega^*_{t,\text{target}}) \) drives the wage inflation in the economy.\(^{25}\)

### 3.4 Monetary policy

I assume a standard Taylor-type interest rate rule for the Central Bank,

\[
i_t = \rho i_{t-1} + (1-\rho) (\phi_\pi \pi_t^p + \phi_y \hat{y}_t) + \phi_\Delta \Delta \hat{y}_t + \nu_t
\]

where \( i_t \equiv -\ln Q_t \) is the nominal yield on a one-period riskless bond, \( \rho \equiv -\ln \beta \) is the household’s discount rate, \( \hat{y}_t \) is the logarithm of the period \( t \) output gap in the economy, and \( \nu_t \) is the exogenous policy shifter. The monetary policy shock \( \nu_t \) is assumed to follow an AR(1) process: \( \nu_t = \rho_\nu \nu_{t-1} + \varepsilon_\nu^t \), where the persistence parameter \( |\rho_\nu| < 1 \) and \( \varepsilon_\nu^t \) is a white noise process with variance \( \sigma_\nu^2 \). The degree to which the Central Bank accommodates exogenous shifts in productivity partly determines the coefficient of the output gap in the Taylor rule. In particular, smaller the parameter \( \phi_y \), the more accommodating is the monetary policy. Since I have already shown empirically that the response of hours and employment turned less countercyclical or sometimes even procyclical after 1984, one can expect to see the parameter \( \phi_y \) turning smaller in magnitude in the later years. It should be noted that a countercyclical response of employment to a technology shock is contingent on the monetary policy being not too accommodative.

\(^{25}\)For the system of log-linearized equations dictating the wage-setting process with nominal rigidity, refer to equations (A.17) through (A.19) in Appendix A.9.
3.5 Equilibrium conditions

I assume that hiring costs take the form of a bundle of final goods given by the same aggregation as the one defining the consumption index. This implies that the demand for each final good is given by 

\[ Y_{it} = \left( \frac{P_{it}}{P_t} \right)^{-\varepsilon} (C_t + G_t H_t) \]

The goods market clearing condition is thus given by

\[ Y_t \equiv \left( \int_0^1 Y_{it}^{\varepsilon+1} \right)^{\frac{1}{\varepsilon+1}} = C_t + G_t H_t \] (3.15)

The aggregate relation between final goods and intermediate input is given by

\[ X_t \equiv \int_0^1 X_{it} d\xi = D_p t Y_t \] (3.16)

where the chasm \( D_p t \equiv \int_0^1 \left( \frac{P_{it}}{P_t} \right)^{-\varepsilon} d\xi \geq 1 \) between the quantities produced and consumed of the different final goods arise due to the price dispersion caused by nominal rigidities. However, in the neighbourhood of the zero-inflation steady state, \( D_p t \approx 1 \), and hence the aggregate production function can be approximated by the following condition,

\[ Y_t = A t E_t^p N_t \] (3.17)

4 Quantitative Analysis

Having put in place a DSGE framework with endogenous effort choice and costly employment adjustment, I now study the quantitative performance of that model.\(^{26}\) Specifically, I will calibrate the parameters of the model to reasonable values often estimated or assumed in the literature, and then check whether structural changes in some of them between the pre and post-1984 periods can generate the empirically observed changes in the business cycle moments.

4.1 Calibration

A typical DSGE model, like the one presented above, contains a lot of parameters. For the ease of exposition, I discuss calibration of the entire set of parameters in four groups: (i) parameters affected by de-unionization, namely, the share of hiring cost in GDP, \( \Theta \) and the wage bargaining power, \( \xi \); (ii) the accommodative stance of monetary policy, \( \phi_y \), which changed during the Volcker-era, and had an impact on the economy’s response to technology shocks; (iii) parameters pertaining to the volatility of the exogenous shocks to technology and monetary policy, namely, \( \sigma_a \) and \( \sigma_{\nu} \), which decreased during Great Moderation; and (iv) other parameters that I will consider to have remained stationary over the period under study.

\(^{26}\)For ease of exposition, I have collected in Appendix A.9 all the model equations with the variables being measured in logarithms of deviations from their zero-inflation steady state values.
4.1.1 Structural Changes due to De-unionization

A fall in hiring cost leading to a rise in the relative dependence on the extensive margin of labour adjustment is the key mechanism under study here. Denoting by $\Theta$ the steady-state share of total hiring cost in real output, i.e., $\Theta \equiv \frac{\bar{G}H}{\bar{Y}}$, the main hypothesis of this paper can thus be captured by a decrease in $\Theta$ in the post-1984 period. I consider a fall in the share of the hiring cost in GDP from 3% in the pre-1983 period to 1% in the post-1984 era. These magnitudes are in line with the estimates of the hiring cost share by Silva and Toledo (2009), and used for calibration in Hagedorn and Manovskii (2008). They estimate hiring cost to be roughly 4.5% of the average quarterly wage. Assuming average wage to be 67% of real output (which is nothing but the labour share in total compensation), the hiring cost as a share of GDP is calibrated to be 3% in the pre-1984 period. Now, union membership rate in private non-farm U.S. industries was about 21% in 1979 after which time it started falling sharply, and reached 1/3 of that value at roughly 7% by 2009. I therefore calibrate the hiring cost share in GDP in the post-1984 era as 1/3 of its pre-1984 value of 3%.\textsuperscript{27}

De-unionization not only affects the hiring cost of workers but also increases the bargaining power of firms. Starting from an equal bargaining power between workers and firms in the pre-1983 period,\textsuperscript{28} I allow the parameter to increase by 67% in the post-1984 period to 0.84, mirroring the fall in union density in private non-farm business sector in the U.S.

4.1.2 Monetary Policy Change

To capture the reduced response of hours on impact of a technology shock in the post-1984 period, it is crucial to allow for parameter $\phi_1$, capturing the degree of accommodation of technology shocks by the monetary policy, to fall in the post-1984 era. I use the values in Smets and Wouters (2007) who estimate the Taylor-rule parameters separately for two periods: 1966 through 1979, and 1984 through 2004, and find that $\phi_1$ in fact decreased from 0.17 to 0.08 between the two periods.\textsuperscript{29} As mentioned earlier, a more accommodative monetary policy counteracts the fall in productivity correlation with hours. In other words, the fall in productivity correlations would have been even larger had there been no structural change in the monetary policy.

---
\textsuperscript{27}It should be noted that Galí and van Rens (2017) also consider a fall in the share of hiring cost from 3% to 1% of GDP, but their calibration choice is motivated by the fall in the gross job separation rate. However, as argued in Appendix A.3, reduction in job separation rate appears to be an unlikely explanation for fall in hiring costs when international evidence is taken into account. Moreover, data on quarterly job flows from Shimer (2012) show that job separation rate fell by only about 10% in the post-1984 era.
\textsuperscript{28}Assuming equal bargaining power, i.e., $\xi = 0.50$, is the standard in the literature.
\textsuperscript{29}It should be noted that the positive response of productivity to an expansionary demand shock (i.e., a negative Taylor-rule shock to the interest rate) is contingent on the monetary policy being not too accommodative. This condition is maintained by the set of estimates in Smets and Wouters (2007).
Table 4.1: Differences in Calibration between Pre- and Post-1984

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
<th>Pre-1984</th>
<th>Post-1984</th>
</tr>
</thead>
<tbody>
<tr>
<td>De-unionization</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Θ</td>
<td>Share of hiring cost in GDP</td>
<td>3%</td>
<td>1%</td>
</tr>
<tr>
<td>ξ</td>
<td>Wage Bargaining Power of Firms</td>
<td>0.50</td>
<td>0.84</td>
</tr>
<tr>
<td>Monetary Policy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>φ_{y}</td>
<td>Response to output gap</td>
<td>0.17</td>
<td>0.08</td>
</tr>
<tr>
<td>Shocks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>σ_{a}</td>
<td>Technology shock volatility</td>
<td>0.45</td>
<td>0.32</td>
</tr>
<tr>
<td>σ_{ν}</td>
<td>Monetary shock volatility</td>
<td>0.24</td>
<td>0.12</td>
</tr>
</tbody>
</table>

4.1.3 Exogenous Shocks: Changes during Great Moderation

For comparability to the literature, I will calibrate the persistences of the productivity and monetary policy shocks to values typically assumed in the literature. In particular, the persistence of the technology shock is assumed to be 0.90, following Galí (2011), and that of the monetary shock is fixed at 0.50, following Galí (2011) and Barnichon (2010). Accounting for the fall in volatility due to Great Moderation, I calibrate the post-1984 standard deviation of the technology shock to be 70% of the pre-1983 value, and that of the monetary shock to be 50% of its corresponding pre-period value. This choice of a reduction of 30% and 50% in the standard deviations of the technology and demand shocks is motivated by the findings in Barnichon (2010).\(^{30}\) Allowing for the shock variances to change in a two-variable SVAR with labour productivity growth and unemployment, Barnichon (2010) finds these magnitudes of drops in the volatilities of technology and demand shocks around the mid-1980s. The calibrated values for the volatilities in the two periods are reported in Table 4.1.

4.1.4 Stationary Parameters

The fourth set of parameters correspond to those which are quite standard in the literature and are arguably not likely to have changed significantly between the pre and post-1984 periods. The complete list of these parameters and their calibrated values are presented in Table 4.2. While most of the parameters are calibrated to some well-established estimates in the literature, the last two parameters in Table 4.2 are somewhat arbitrarily chosen. For example, the curvature of the convex average hiring cost function is assumed to be quadratic (implying \( γ = 1 \)), but the literature reports values for \( γ \) ranging between 0.6 and 2.4. Similarly, the value of \( φ \), denoting the degree of increasing marginal disutility from higher effort, is chosen arbitrarily because of lack of empirical estimates in the

\(^{30}\)As external evidence, in Appendix A.10 I show that the volatility of the monetary shock as measured by Romer and Romer (2004) empirically decreased by about 50%. 

28
literature. However, as a robustness check in Appendix A.11, I show that assuming different values for these two parameters do not significantly alter the main quantitative findings from the model.

### Table 4.2: Calibration of Time-Invariant Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>0.99</td>
<td>Real risk-free annual interest rate ( \simeq 3% )</td>
</tr>
<tr>
<td>( \varepsilon )</td>
<td>10.0</td>
<td>Mark-up over marginal cost ( \simeq 11% )</td>
</tr>
<tr>
<td>( \psi )</td>
<td>0.67</td>
<td>Share of non-labour input in total compensation</td>
</tr>
<tr>
<td>( \theta_p )</td>
<td>0.75</td>
<td>Calvo nominal rigidity; Galí (2011)</td>
</tr>
<tr>
<td>( \theta_w )</td>
<td>0.75</td>
<td>Nominal wage rigidity; Galí (2011)</td>
</tr>
<tr>
<td>( \delta )</td>
<td>0.10</td>
<td>Quarterly gross job separation rate; Shimer (2012)</td>
</tr>
<tr>
<td>( \phi_\pi )</td>
<td>1.70</td>
<td>Taylor rule response to inflation; Smets and Wouters (2007)</td>
</tr>
<tr>
<td>( \phi_{\Delta y} )</td>
<td>0.20</td>
<td>Taylor rule response to output gap growth; Smets and Wouters (2007)</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.80</td>
<td>Persistence in monetary policy; Smets and Wouters (2007)</td>
</tr>
<tr>
<td>( \rho_a )</td>
<td>0.90</td>
<td>Persistence of technology shock; Galí (2011)</td>
</tr>
<tr>
<td>( \rho_\nu )</td>
<td>0.50</td>
<td>Persistence of monetary policy shock; Galí (2011), Barnichon (2010)</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>1.00</td>
<td>Quadratic hiring cost</td>
</tr>
<tr>
<td>( \phi )</td>
<td>1.50</td>
<td>Increasing marginal disutility from effort</td>
</tr>
</tbody>
</table>

### 4.2 Quantitative Performance of Model

Having calibrated the model parameters separately for the pre and post-1984 sub-periods, I will now examine how well the model can match the main phenomenon of vanishing procyclicality of labour productivity, along with other changes in business cycle moments like the rising relative volatility of employment, the falling procyclicality of real wages, etc.

#### 4.2.1 Business cycle moments

There are multiple parameter changes in the calibration for the two sub-periods. It is therefore natural to ask what role does each parameter change play in explaining the differences in the business cycle moments. For that purpose, I will introduce the parameter changes in Table 4.1 one at a time.
Table 4.3: Changes in Business Cycle Moments due to De-unionization

<table>
<thead>
<tr>
<th>Business Cycle Moments</th>
<th>Changes in Moments between Pre &amp; Post 1984 Periods</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data (1)</td>
</tr>
<tr>
<td>Labour Productivity Correlations</td>
<td></td>
</tr>
<tr>
<td>Output: $Corr(y_t, l_p_t)$</td>
<td>-0.40</td>
</tr>
<tr>
<td>Employment: $Corr(n_t, l_p_t)$</td>
<td>-0.51</td>
</tr>
<tr>
<td>Hiring Flows: $Corr(h_t, l_p_t)$</td>
<td>-0.53</td>
</tr>
<tr>
<td>Relative Volatility of Employment</td>
<td></td>
</tr>
<tr>
<td>Output: $s.d.(n_t) / s.d.(y_t)$</td>
<td>+46%</td>
</tr>
<tr>
<td>Conditional $Corr(n_t, l_p_t)$</td>
<td></td>
</tr>
<tr>
<td>Technology Shock</td>
<td>-0.06</td>
</tr>
<tr>
<td>Demand Shock</td>
<td>-1.24</td>
</tr>
<tr>
<td>Conditional $Corr(y_t, l_p_t)$</td>
<td></td>
</tr>
<tr>
<td>Technology Shock</td>
<td>+0.19</td>
</tr>
<tr>
<td>Demand Shock</td>
<td>-1.21</td>
</tr>
<tr>
<td>Real Wage Correlations</td>
<td></td>
</tr>
<tr>
<td>Output: $Corr(y_t, w_t)$</td>
<td>-0.34</td>
</tr>
<tr>
<td>Employment: $Corr(n_t, w_t)$</td>
<td>-0.34</td>
</tr>
<tr>
<td>Labour Productivity: $Corr(l_p_t, w_t)$</td>
<td>-0.10</td>
</tr>
</tbody>
</table>

Note: To maintain comparability with the existing literature, all moments have been calculated on quarterly Hodrick-Prescott-filtered variables for both data and model-simulated series. Baseline in column (2) refers to the model calibration where all the changes in the parameters in Table 4.1 have been implemented. To understand the driving force behind the changes in the moments in the Baseline case, columns (3) through (5) provide different counterfactual scenarios where one channel of parameter change is shut down at a time.

De-unionization

In Table 4.3, I first see how de-unionization alone performs in capturing the changes in the moments. Column (1) reports the empirically observed changes in business cycle moments between pre and post-1984 periods, while column (4) reports the total change explained by de-unionization. However, since a fall in union density is captured by two parameter changes, namely, a fall in the share of hiring cost in GDP, $\Theta$ and a rise in the firms’ bargaining power, $\xi$, I also show the relative contribution of these two channels in the total effect of de-unionization in columns (2) and (3) respectively. Comparing


columns (1) and (4) in Table 4.3 one can see that the parameter changes attributed to de-unionization perform really well in matching the empirically observed drop in productivity correlations, both for unconditional correlations as well as conditional on technology and demand shocks. For the relative volatility of employment, the baseline calibration of the model captures more than half of the total rise in the data. Also, most of the changes in these moments can be attributed to the change in the hiring cost parameter, which is the central mechanism discussed in the paper.

Finally, the cyclical properties of real wages have also changed in the U.S. around the same time as the productivity puzzle and the Great Moderation. The model’s ability to capture the changes in the cyclical wage correlations is primarily driven by the change in the bargaining power parameter. This importance of the bargaining parameter in determining wage dynamics is not surprising, given that the parameter directly enters the real wage equation (3.13). Regarding the volatility of real wages, the current model predicts a fall in the post-1984 era. However, empirical evidence on wage volatility has been mixed. Champagne, Kurmann, and Stewart (2017) discuss how average hourly wage volatility in the U.S. has diverged across different data sources: the Labor Productivity and Costs (LPC) program, the Current Population Survey (CPS), and the Current Employment Statistics (CES). Supplements and irregular earnings of high-income workers, included only in the LPC, drive the rising volatility in LPC earnings as opposed to CPS and CES based measures. One way to match the rising volatility of real wages (e.g., Champagne and Kurmann (2013) and Nucci and Riggi (2013)) in the current model would be to introduce real wage rigidity and let it decline in the post-1984 period. This can be done by introducing wage indexation to past inflation, or through endogenous real wage rigidity that depends on the size of the wage bargaining set in equilibrium. Lemieux, Macleod, and Parent (2009) discuss the rising importance of performance wages in the U.S. economy, which can also help explain the rising wage volatility. These channels are however absent in the current version of the model, and remain a task for future research.

31 A real wage rigidity decline in the post-1984 period is not to be confused with increasing nominal wage rigidity during the same period. Using Bayesian estimation, Smets and Wouters (2007) find nominal wage rigidity to have gone up after the mid-1980s, although the increase is not statistically significant. Under increasing nominal wage rigidity, firms cannot change wages as frequently as they want and need to rely on adjusting employment more. This channel of more employment adjustment further depresses the procyclicality of productivity and increases the relative employment volatility. This mechanism is highlighted in Gu and Prasad (2018).
Table 4.4: Changes in Business Cycle Moments between Pre & Post 1984 Periods

<table>
<thead>
<tr>
<th>Business Cycle Moments</th>
<th>Changes in Moments between Pre &amp; Post 1984 Periods</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data (1)</td>
<td>De-unionization (2)</td>
</tr>
<tr>
<td><strong>Labour Productivity Correlations</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output: $\text{Corr}(y_t, lp_t)$</td>
<td>-0.40</td>
<td>-0.46</td>
</tr>
<tr>
<td>Employment: $\text{Corr}(n_t, lp_t)$</td>
<td>-0.51</td>
<td>-0.39</td>
</tr>
<tr>
<td>Hiring Flows: $\text{Corr}(h_t, lp_t)$</td>
<td>-0.53</td>
<td>-0.47</td>
</tr>
<tr>
<td><strong>Relative Volatility of Employment</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output: $\text{Corr}(n_t, lp_t)$</td>
<td>+46%</td>
<td>+27%</td>
</tr>
<tr>
<td><strong>Conditional $\text{Corr}(n_t, lp_t)$</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology Shock</td>
<td>-0.06</td>
<td>-0.07</td>
</tr>
<tr>
<td>Demand Shock</td>
<td>-1.24</td>
<td>-0.71</td>
</tr>
<tr>
<td><strong>Conditional $\text{Corr}(y_t, lp_t)$</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology Shock</td>
<td>+0.19</td>
<td>-0.07</td>
</tr>
<tr>
<td>Demand Shock</td>
<td>-1.21</td>
<td>-0.87</td>
</tr>
<tr>
<td><strong>Real Wage Correlations</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output: $\text{Corr}(y_t, w_t)$</td>
<td>-0.34</td>
<td>-0.16</td>
</tr>
<tr>
<td>Employment: $\text{Corr}(n_t, w_t)$</td>
<td>-0.34</td>
<td>-0.25</td>
</tr>
<tr>
<td>Labour Productivity: $\text{Corr}(lp_t, w_t)$</td>
<td>-0.10</td>
<td>-0.03</td>
</tr>
</tbody>
</table>

**Note:** To maintain comparability with the existing literature, all moments have been calculated on quarterly Hodrick-Prescott-filtered variables for both data and model-simulated series. Baseline in column (2) refers to the model calibration where all the changes in the parameters in Table 4.1 have been implemented. To understand the driving force behind the changes in the moments in the Baseline case, columns (3) through (5) provide different counterfactual scenarios where one channel of parameter change is shut down at a time.

**Accommodative monetary policy**

In Table 4.4, column (3) shows that more accommodative monetary policy by the Federal Reserve cannot induce large changes in the productivity moments, and most of those changes actually go against the empirically observed direction of moment changes. As argued in Section 2.2.2, allowing for a more accommodating monetary policy means that conditional on a positive technology shock when output gap increases, the contraction induced through monetary policy is less severe. This implies that with a lower $\phi_y$, output and employment increases more in response to a given positive technology...
shock, thereby increasing the cyclical correlation of productivity with both output and labour input. This corroborates the empirical finding in Section 2.2.2 that the negative impulse response of hours worked to a positive technology shock is muted after the mid-1980s. To summarize, in absence of the more accommodative stance of the Federal Reserve under Volcker, the drop in productivity correlations would have been even more severe.

Reduction in shock volatility

Column (4) of Table 4.4 shows that the model’s ability to match the changes in the business cycle moments is not contingent on the drop in volatilities of the exogenous shocks during Great Moderation. There are two aspects to this observation. First, uniform reduction of volatilities of shocks per se cannot be expected to change correlation between variables. In that sense, this finding is not surprising. However, in the calibration, the reduction in technology shock volatility was smaller than the fall in demand shock volatility. This mechanically increases the importance of technology shock in the post-1984 period. Since technology shocks induce countercyclicality of productivity with labour input, this should explain part of the vanishing procyclicality of productivity. This mechanism was highlighted in Barnichon (2010). Nevertheless, one can see from column (4) that even this channel of non-uniformity in volatility reduction could not explain any significant amount of the productivity puzzle.

One of the main indicators that substantiated the role of increased flexibility in the labour market as the key driving factor behind the labour productivity puzzle was the drastic change in the correlations of productivity conditional on demand shocks. If it were merely the case of changing relative importance of technology and demand shocks that explained the fall in the unconditional productivity correlations (as argued in Barnichon (2010)), then structural changes like the decline of hiring costs would not have been the significant channels for explaining the puzzle. The substantial fall in the productivity correlations conditional on the monetary policy shock in the model corroborates that empirical finding.

The finding that fall in productivity correlations conditional on a demand shock is driving the unconditional moments implies that demand shock should be the main source of variation for output and employment dynamics over the business cycle. This is empirically corroborated by the dominance of non-technology shocks in explaining the total cyclical volatility of per capita hours in Figure A.14. Since the only non-technology or demand shock in the model is the monetary policy shock, it is the dominant source of business cycle variation here. However, it should be noted that Smets and Wouters (2007) find that in the presence of a variety of demand shocks, e.g., exogenous spending shock, risk premium shock, investment-specific technology shock, etc., the role of monetary policy shock is quite limited in the cyclical variation of output. Thus, the predominant role played by the monetary policy shock in this model should be thought as a consequence of the loading of all variation due to various demand shocks onto a single monetary policy shock.
4.2.2 Impulse Response Functions

One check for quantitative validity of the model is to be able to generate impulse responses that are in line with the empirically observed ones. Figure 4.1 shows how the impulse response of employment rate to a positive technology shock (panel (a)), and that of average labour productivity to a contractionary monetary policy shock (panel (b)) have both become muted in the post-1984 period. These changes in model-implied impulse responses are indeed qualitatively same as those observed empirically (discussed in Section 2.2.2).

It is interesting to know what parameter changes in the model are driving the changes in the impulse responses to shocks in the post-1984 period. While the muted negative response of employment to technology shock is almost entirely driven by the fall in $\phi_y$ (which implies a more accommodative monetary policy in the post-1984 era), the reduced magnitude of rise in productivity due to a contractionary monetary policy shock is caused by the fall in hiring cost $\Theta$. These changes in impulse responses once again prove that the labour productivity puzzle cannot be explained by the rise in the relative importance of technology shock (because the countercyclical property of technology shocks became muted post 1984), rather by structural changes in the economy that caused productivity to respond less to demand shocks over the business cycle.

![Figure 4.1: Model-implied Impulse Responses to Technology and Demand Shocks](image)

Note: Model-generated Impulse Response Functions (IRF) for the pre-1984 period are in blue, and the post-1984 IRF’s are in red dashed lines. Pre- and post-1984 calibrations of parameters correspond to all parameter changes listed in Table 4.1.

5 Other plausible explanations: Lack of evidence

Having provided a coherent structural explanation for a host of changes that occurred in the correlation and volatility patterns of key economic variables around the mid-1980s in the U.S., I will now try to argue that some of the other plausible channels that have been explored in the literature as potential explanations for the productivity puzzle do not hold up to closer empirical scrutiny.
5.1 Rise of service sector

The rise of the service sector and the corresponding decline in the share of value added and employment for the manufacturing industries could have led to the fall in the labour productivity correlations.

One possible channel is the so-called composition effect — if the service sector has a labour productivity which is less correlated with output and hours (arguably due to more flexible work hours), then a simple compositional shift in the share of value-added or employment towards services can explain the decline in the aggregate productivity correlations. However, the labour productivity correlations in Table 5.1 clearly show that the two sectors had strikingly similar correlations even before the mid-1980s, and both of them experienced a similar drop in labour productivity correlations over the business cycle. Moreover, this compositional shift towards services has been too gradual (see panels (a) and (b) of Figure 5.1) to explain the sudden drop in the productivity correlations. This refutes the claim that a simple compositional shift towards a service economy was responsible for the vanishing procyclicality of aggregate productivity.

Table 5.1: Labour Productivity Correlations in Manufacturing & Services

<table>
<thead>
<tr>
<th>Sector</th>
<th>With Output</th>
<th>With Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing</td>
<td>0.63</td>
<td>0.40</td>
</tr>
<tr>
<td>Services</td>
<td>0.68</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Note: Data is sourced from annual KLEMS dataset between 1947 and 2010 by aggregating industry-level non-additive chained indices according to the cyclical expansion method developed in Cassing (1996). Results are robust to using annual sectoral dataset from BEA, compiled by Herrendorf, Herrington, and Valentinyi (2015).
The second channel through which the rise of the service sector can contribute towards falling aggregate productivity correlations is the substitution effect — if there is a larger share of services intermediate inputs in the economy then the labour productivity of all sectors will mimic that of the services sector.\footnote{This idea of evolving input-output structure of the economy leading to switch in cyclicality of productivity can be found in Huang, Liu, and Phaneuf (2004), who explain the switch in the cyclicality of real wages in the post-War period.} While there has indeed been an increase in share of services intermediate inputs since early 1980s (see Figure 5.1c), it is not the case that the manufacturing sector started to have similar productivity correlations as the service sector only after the increased use of services intermediate inputs. Moreover, looking at a cross-section of 31 U.S. industries in Figure 5.2, I do not find any negative relation between the rise in the share of services intermediate input usage and the change in the labour productivity correlations. Although all industries, except agriculture, witnessed a rise in the share of services intermediate inputs in the post-1984 period, this rise was not correlated with the industry-specific fall in the productivity correlations. All these pieces of evidence essentially refute both the composition effect and the substitution effect channels of the rise of the service sector as an explanation for the fall in labour productivity correlations.

5.2 Growing share of intangible investment

One explanation that is provided in the literature for the drop in labour productivity correlations is the mismeasurement of output (see McGrattan and Prescott (2012), henceforth MP). The argument is that
if a part of output is not measured and if this omitted portion of output is more positively correlated with labour input than the measured part, then the measured labour productivity correlation can be lower than the true one. MP argue that intangible capital is one such source of mismeasurement in output, and so the increased use of intangible capital in recent years can generate countercyclical labour productivity.

For the argument to hold empirically, one needs intangible investment to rise markedly around the mid-1980s. However, MP analyzes the U.S. business cycle only between 2004 and 2011. Nevertheless, it is important to corroborate whether their explanation is supported by the data when the correct time-period is considered. Specifically, I want to check if the rise in intangible investment across U.S. industries around the mid-1980s is positively correlated with the magnitude of the fall in labour productivity correlations.

![Graph showing changes in share of IPP in total capital stock and labour productivity correlation.](image)

**Figure 5.3: Changes in Share of IPP in Total Capital Stock & Labour Productivity Correlation**

*Note:* Data for labour productivity correlations at the industry-level is sourced from the annual KLEMS dataset, and that for the IPP capital share is sourced from BEA. Industry codes from the two datasets were matched to create a consistent set of 24 U.S. industries. Time-changes refer to the difference between the average values in the post-1984 (1984-2010) and the pre-1984 period (1969-1983). Regression is weighted by the time-average of industry employment, depicted by the size of the bubbles. The p-value of the estimated slope is reported in parentheses. The BK bandpass filter between 2 and 8 years has been used to extract the cyclical component of the variables. Result is robust to using other filters and time-horizons.

MP defines intangible capital as the “...accumulated know-how from investing in research and development, brands, and organizations, which is for the most part expensed by companies rather than capitalized.” Keeping this definition in mind, any empirical measure of intangible investment is difficult to find, but the closest one can get in available data is to look at investment in intellectual property products (IPP). IPP contains research and development, computer software and databases, and other products like artistic originals.\(^{33}\) While IPP investment picked up in the late 1970s and early 1980s

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\(^{33}\)For a detailed discussion on the measure of IPP capital used, please refer to Appendix A.12. Wang (2014) considers
across almost all industries, I do not find a significant correlation between the rise in IPP capital share and the drop in labour productivity correlations in the cross-section (see Figure 5.3).

5.3 Aggregate versus sectoral shocks

Aggregate productivity can be boosted through easier reallocation of factors of production across firms and industries. In fact, there is a large literature discussing the inefficiency and lost productivity due to factor misallocation (see for example, Hsieh and Klenow (2009)). The basic intuition is that when productive factors shift to firms or industries with higher marginal products of inputs, the overall economy generates more output with the same amount of inputs, even without any technological progress. Thus, if frictions impeding the efficient allocation of resources became less important during economic downturns since the mid-1980s then measured productivity can become less procyclical. More flexible labour markets with lower frictions in hiring and firing (discussed above in Section 2.2), and deeper financial markets aiding capital movement can contribute to such countercyclical reallocation of resources in the last three decades.

Using the finding in Foerster, Sarte, and Watson (2011) that sectoral reallocation shocks became more important for business cycles in the U.S. economy over the recent years, Garin, Pries, and Sims (2018) claim that more efficient reallocation in the post-1984 period has led to less procyclical productivity. Their claim hinges on separately identifying aggregate economy-wide shocks from sector-specific shocks, and empirically finding that the volatility of aggregate shocks have shrunk drastically in the post-1984 era. They use monthly sectoral U.S. data from the Index of Industrial Production (IIP), which covers mostly the U.S. manufacturing sector only. I replicate the analysis using industry-level data from various sources (like the BEA, the KLEMS, and the Current Employment Statistics (CES) data) that covers the entire U.S. economy. While there is considerable heterogeneity across datasets in how much of the total variation in output and hours growth is explained by sectoral shocks, I find that, regardless of the dataset, the relative importance of sectoral shocks have increased dramatically in the post-1984 period. However, this robustness is not maintained when the number of industry classifications is large. For example, when the 31-industry classification from KLEMS dataset, or the 20-industry classification from IIP data is considered, there is no clear pattern of sectoral shocks becoming more important in the later decades.

Even if it is granted that reallocation of factors of production across different sectors of the economy has improved since the mid-1980s, it should be noted that sectoral measures of TFP and labour productivity already take into account the intra-industry reallocation of resources. Since a majority of U.S. industries have individually experienced a decline in procyclicality of measured productivity (as

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34Aggregate shock is identified as the first principal component in the data on sectoral growth rate of output or employment. Refer to Appendix A.13 for details on the identification strategy.

35See Appendix A.13 for details of analysis showing the relative importance of sector-specific shocks in the U.S. economy.
shown in Section 2), it is likely that intra-industry reallocation across firms has been more important than inter-industry reallocation. Therefore, while there is certainly a predominance of industry-specific shocks in the last three decades, there is reason to doubt that inter-industry reallocations have an important role to play in explaining the drop in productivity correlations.

In this context, it is also important to note that sectoral labour reallocation is also often cited as one of the major reasons for jobless recoveries after the last two recessions. This argument typically draws from the evidence in Groshen and Potter (2003) who argue that increased permanent relocation of workers from some industries to others have stalled growth in jobs. Since jobless recoveries tend to exacerbate the negative correlation between productivity and hours (although they increase the correlation between productivity and output), it is important to consider this channel of sectoral reallocation. However, Aaronson, Rissman, and Sullivan (2004) show that Groshen and Potter’s findings are very sensitive to the exact period over which the measure of reallocation is computed, the dating of business cycle turning points, and the weighting of the industries. In fact, using an alternative measure of sectoral reallocation developed by Rissman (1997) they show that reallocation of employment across industries has declined, not increased, over the past two business cycles.

To summarize, the evidence for increased inter-sectoral labour reallocation as an important explanation for either the vanishing procyclicality of labour productivity or jobless recoveries, appears to be less than convincing.

6 Conclusion

Why did productivity suddenly start becoming less procyclical during the mid-1980s? This is the research question that this paper tries to answer. A decomposition of measured productivity into factor utilization and a utilization-adjusted productivity component reveals that the fall in productivity correlations is driven by a lower dependence on factor hoarding. Changes in responses of the U.S. economy to technology and demand shocks also point towards some structural change in the factor markets that made adjusting factors along the extensive margin less costly. This paper identifies rapid decline in union power since the early-1980s as the key structural change in the labour market that made hiring and firing of workers easier for firms. Using cross-sectional evidence from U.S. industries and states, and also international evidence from OECD countries, it is argued that more intense de-unionization is associated with a deeper fall in the cyclical productivity correlations. Moreover, lower dependence on labour hoarding through effort adjustment in the face of higher labour market flexibility is shown to imply rising relative volatility of employment, and this rise is also correlated with the fall in union density and productivity correlations across U.S. industries. Understanding the reduced role of labour market institutions like unions in influencing business cycle properties of key macroeconomic variables is the key contribution of this paper.

The paper has also pointed out the absence of empirical evidence for other interesting and plausible theoretical explanations for the drop in productivity correlations. In particular, I have shown
that neither the rise of the service sector in terms of value-added or its use as intermediate input can explain the phenomenon. Moreover, the increased use of intangible capital, and the increased variation of sectoral shocks relative to aggregate shocks that facilitate factor reallocation to more productive sectors during recessions, do not seem to have empirical validity as possible explanations.

A standard New Keynesian model with endogenous effort choice in the face of costly hiring of workers can not only generate the empirically observed changes in the business cycle moments of output, employment and productivity, but also qualitatively match the changes in the impulse responses of these variables to technology and demand shocks. These structural changes are not always consistent with the phenomenon of jobless recoveries in the U.S., e.g., the fall in cyclical correlation of labour productivity with output that is brought about by falling hiring costs militates against jobless recoveries. Hence it seems more likely that jobless or slow recoveries should be explained by other factors such as occupational or sectoral reallocation, that are not the main drivers behind the productivity puzzle.

Important policy implications like using a more accommodative monetary policy to generate more jobs during recovery booms follow immediately from the central thesis of this article. Such a policy will also help in making productivity more procyclical again. However, there are potential downsides of too much accommodation of positive technology shocks by the monetary authority as it may lose its power to fight recessions by lowering interest rates further during economic downturns. Therefore, there is a debate regarding whether maintaining countercyclical productivity in the long run is welfare-improving or not. Future research can shed light on these welfare implications of the productivity puzzle.

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A Appendix

A.1 Robustness to Choice of Filters and Datasets

In this section, I will present the cyclical correlations and volatilities of different variables using different datasets and time-series filters. In particular, the three datasets considered here are as follows: (i) Labor Productivity and Costs (LPC) dataset published by the Bureau of Labor Statistics (BLS) that contains both quarterly and annual data on output, hours, employment and labour productivity for the U.S. business sector; (ii) John G. Fernald’s TFP dataset which contains quarterly and annual data on growth rates of TFP, factor utilization rate and utilization-adjusted TFP for the U.S. business sector; and (iii) KLEMS dataset (compiled by Jorgenson, Ho and Samuels) that contains annual data on output, hours, employment, labour productivity and growth rate of TFP for the aggregate U.S. economy. Since the TFP data is only available in growth rates, I could only use quarterly and annual growth rates as the filter for the analysis involving TFP. Apart from growth rates, I have considered two other time-series filters that are regularly used for extracting business cycle dynamics from macro-data — (i) Hodrick and Prescott (1997) filter, with the smoothing parameter being 1600 for quarterly data and 6.25 for annual data, following Ravn and Uhlig (2002), and (ii) bandpass filter, extracting the dynamics between 6 and 32 quarters or between 2 and 8 years for quarterly or annual data respectively. To compare the two sub-periods — before and after the mid-1980s, I have presented all the moments in Tables A.1 through A.3 separately, and also indicated the statistical significance of the difference between the two sub-periods.

### Table A.1: Cyclical Correlation of Average Labour Productivity (Output per Hour)

<table>
<thead>
<tr>
<th>Dataset &amp; Filter Choice</th>
<th>With Output</th>
<th></th>
<th></th>
<th>With Hours</th>
<th></th>
<th></th>
<th>With Employment</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: LPC Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hodrick-Prescott ($\lambda=1600$)</td>
<td>0.61</td>
<td>-0.01</td>
<td>-0.62</td>
<td>0.15</td>
<td>-0.53</td>
<td>-0.68</td>
<td>0.05</td>
<td>-0.59</td>
<td>-0.64</td>
</tr>
<tr>
<td>BK-Bandpass: 6-32 Qtrs.</td>
<td>0.56</td>
<td>-0.03</td>
<td>-0.59</td>
<td>0.12</td>
<td>-0.53</td>
<td>-0.65</td>
<td>0.01</td>
<td>-0.58</td>
<td>-0.59</td>
</tr>
<tr>
<td>Quarterly Growth Rate</td>
<td>0.71</td>
<td>0.53</td>
<td>-0.18</td>
<td>0.02</td>
<td>-0.34</td>
<td>-0.36</td>
<td>-0.02</td>
<td>-0.33</td>
<td>-0.31</td>
</tr>
<tr>
<td>4-Quarter Growth Rate</td>
<td>0.63</td>
<td>0.23</td>
<td>-0.40</td>
<td>0.08</td>
<td>-0.37</td>
<td>-0.45</td>
<td>-0.04</td>
<td>-0.37</td>
<td>-0.34</td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>0.64</td>
<td>0.16</td>
<td>-0.48</td>
<td>0.12</td>
<td>-0.40</td>
<td>-0.52</td>
<td>-0.03</td>
<td>-0.40</td>
<td>-0.37</td>
</tr>
<tr>
<td><strong>Panel B: KLEMS Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hodrick-Prescott ($\lambda=6.25$)</td>
<td>0.35</td>
<td>-0.02</td>
<td>-0.37</td>
<td>-0.22</td>
<td>-0.62</td>
<td>-0.40</td>
<td>-0.28</td>
<td>-0.60</td>
<td>-0.32</td>
</tr>
<tr>
<td>BK-Bandpass: 2-8 Years</td>
<td>0.42</td>
<td>0.32</td>
<td>-0.10</td>
<td>-0.17</td>
<td>-0.52</td>
<td>-0.35</td>
<td>-0.33</td>
<td>-0.42</td>
<td>-0.10</td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>0.53</td>
<td>0.22</td>
<td>-0.31</td>
<td>-0.10</td>
<td>-0.32</td>
<td>-0.22</td>
<td>-0.14</td>
<td>-0.24</td>
<td>-0.10</td>
</tr>
</tbody>
</table>

36 There are two choices for the bandpass filter — (i) the Baxter and King (1999) (BK) filter, and (ii) the Christiano and Fitzgerald (2003) (CF) filter. I use the BK filter for any analysis involving correlations. This is because the BK filter, unlike the CF filter, does not introduce any time- or frequency-dependent phase shift in the filtered data (see Iacobucci and Nouillez (2005)). While using the CF filter might introduce spurious correlations in the filtered data, the BK filter distorts the amplitude or volatility of the extracted cycle. This prompts me to use the CF filter for the analysis involving cyclical volatility.
Table A.2: Cyclical Volatility of Output, Hours & Employment

<table>
<thead>
<tr>
<th>Dataset &amp; Filter Choice</th>
<th>s.d.(Output)</th>
<th>s.d.(Hours)</th>
<th>s.d.(Employment)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: LPC Data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hodrick-Prescott (λ=1600)</td>
<td>2.42</td>
<td>1.41</td>
<td>0.58</td>
</tr>
<tr>
<td>CF-Bandpass: 6-32 Quarters</td>
<td>2.33</td>
<td>1.36</td>
<td>0.58</td>
</tr>
<tr>
<td>4-Quarter Growth Rate</td>
<td>0.94</td>
<td>0.59</td>
<td>0.63</td>
</tr>
<tr>
<td><strong>Panel B: KLEMS Data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hodrick-Prescott (λ=6.25)</td>
<td>1.68</td>
<td>0.94</td>
<td>0.56</td>
</tr>
<tr>
<td>CF-Bandpass: 2-8 Years</td>
<td>1.65</td>
<td>1.02</td>
<td>0.62</td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>2.73</td>
<td>1.89</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Figure A.1: Cyclical Volatility of Output, Hours & Employment

(a) Qtrly. Output Growth  
(b) Qtrly. Hours Growth  
(c) Qtrly. Employment Growth

Table A.3: Relative Cyclical Volatility of Hours & Employment

<table>
<thead>
<tr>
<th>Dataset &amp; Filter Choice</th>
<th>s.d.(Hours)/s.d.(Output)</th>
<th>s.d.(Employment)/s.d.(Output)</th>
<th>s.d.(Employment)/s.d.(Hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: LPC Data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hodrick-Prescott (λ=1600)</td>
<td>0.80</td>
<td>1.18</td>
<td>1.47</td>
</tr>
<tr>
<td>CF-Bandpass: 6-32 Quarters</td>
<td>0.81</td>
<td>1.08</td>
<td>1.33</td>
</tr>
<tr>
<td>4-Quarter Growth Rate</td>
<td>0.76</td>
<td>1.02</td>
<td>1.35</td>
</tr>
<tr>
<td><strong>Panel B: KLEMS Data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hodrick-Prescott (λ=6.25)</td>
<td>0.95</td>
<td>1.26</td>
<td>1.33</td>
</tr>
<tr>
<td>CF-Bandpass: 2-8 Years</td>
<td>0.95</td>
<td>1.11</td>
<td>1.17</td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>0.83</td>
<td>1.01</td>
<td>1.22</td>
</tr>
</tbody>
</table>

46
A.2 Plausible Channels of Increased Labour Market Flexibility

De-unionization, as discussed in the paper, may not be the only factor that can lead to increased labour market flexibility. One such possible cause of increasing employment turnover is the rise in online job-search platforms, which reduces the hiring cost by making it much easier to match workers and jobs. Moreover, the improved efficiency of online matching between specific worker and job types could also mean that firms need to terminate less workers who do not fit well with the job, thereby reducing the firing cost for firms. However, this is unlikely to have triggered the switch in the productivity correlations in the mid-1980s because internet recruitment service providers did not begin their journey until the mid-1990s.

The increased use of temporary workers is another likely reason for reduction in employment adjustment cost. Jalón, Sosvilla-Rivero, and Herce (2017) argue that the countercyclicality of labour productivity in Spain was driven by the 1984 legislative reform that increased the importance of temporary workers in the Spanish economy. Daruich, Addario, and Saggio (2017) also study the implications of a similar 2001-reform of lifting constraints on employment of temporary contract workers in Italy.

\begin{figure}
\centering
\includegraphics[width=0.5\textwidth]{figure_a2.pdf}
\caption{Share of Part-time Employment in the U.S. (1968-2017)}
\end{figure}

*Note:* Data is sourced from Labor Force Statistics (LFS) of the Current Population Survey (CPS). Part-time employment is defined as less than 35 hours of work per week.

For the U.S. it is difficult to ascertain the role of temporary workers in the increased flexibility of labour markets due to lack of suitable data that dates back long enough, e.g., employment data for the temporary help services industry from the Current Employment Statistics (CES) database of BLS dates back only till 1990. Although Carey and Hazelbaker (1986) show that employment growth in the temporary help industry increased sharply immediately after the 1982 recession, which lines up well with the timing of the switch in labour productivity correlations, Schreft and Singh (2003) show that temporary and part-time hiring and overtime — collectively known as ‘just-in-time hiring’ — has gained in importance only since the 1991 recession in the U.S. However, for the U.S., I study the time series of the share of part-time workers (see Figure A.2) and do not find any noticeable upsurge, if not an actual plateauing, in the share of part-time workers around the mid-1980s.
A.3 International Evidence for De-unionization

In Table A.4, I present changes between the pre and post-1984 periods in the cyclical properties of some labour market variables from selected OECD countries. The cyclical moments reported are changes in (i) correlation of labour productivity with output, (ii) correlation of labour productivity with hours worked, and (iii) relative volatility of employment to output. Variables capturing labour market structure are changes in (i) unionization rate, and (ii) gross job separation rate.

<table>
<thead>
<tr>
<th>Country</th>
<th>Δ Correlation of Labour Productivity</th>
<th>S.D. (Employment)</th>
<th>Labour Market Structure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>With Output</td>
<td>With Hours</td>
<td>S.D. (Output)</td>
</tr>
<tr>
<td>U.S.A.</td>
<td>-0.54</td>
<td>-0.62</td>
<td>32%</td>
</tr>
<tr>
<td>Australia</td>
<td>-0.44</td>
<td>-0.48</td>
<td>73%</td>
</tr>
<tr>
<td>U.K.</td>
<td>-0.39</td>
<td>-0.46</td>
<td>41%</td>
</tr>
<tr>
<td>Spain</td>
<td>-1.37</td>
<td>-0.74</td>
<td>317%</td>
</tr>
<tr>
<td>Ireland</td>
<td>-0.44</td>
<td>-0.21</td>
<td>44%</td>
</tr>
<tr>
<td>Italy</td>
<td>-0.09</td>
<td>-0.16</td>
<td>71%</td>
</tr>
<tr>
<td>Norway</td>
<td>-0.35</td>
<td>-0.12</td>
<td>47%</td>
</tr>
<tr>
<td>Canada</td>
<td>0.01</td>
<td>0.09</td>
<td>-22%</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.01</td>
<td>-0.03</td>
<td>59%</td>
</tr>
</tbody>
</table>

Note: All changes are between the post and pre-1984 periods. Labour productivity is defined as real GDP per hour worked. De-trending of variables has been done using the HP-filter. Quarterly data on output and hours between 1960 and 2010 for all countries (except Spain) are taken from OECD Economic Outlook Database, collected by Ohanian and Raffo (2012). Annual data for Spain between 1950 and 2017 is sourced from the Conference Board Total Economy Database. Union density data are sourced from OECD Annual Trade Union Density Dataset. Since internationally comparable data on job flows are not available before 1980s, changes in job separation rate are calculated as the difference between the average rate between 2002 through 2007, and that between 1985 through 1990, as reported in Elsby, Hobijn, and Ahin (2015).

Galí and van Rens (2017) claim that the main driver of falling labour market frictions in the U.S. labour market was the drop in job separation rate. They argue that because of a substantial drop in the gross job destruction rate, firms need to hire much less new workers to maintain the level of employment. This reduced hiring activity implies lower cost of employment adjustment in equilibrium, thereby leading to more countercyclical productivity. While this channel of reduction in employment adjustment cost is certainly feasible for the U.S., a cursory glance at the international evidence, presented in Table A.4, points towards de-unionization being more closely related to vanishing procyclicality of productivity than a decrease in job separation rate. Of the 9 countries presented here, only Ireland experienced a notable decrease in the job separation rate along with decreasing cyclical correlation of labour productivity. Nevertheless, Ireland also experienced a 21% drop in union density, and hence the exact source of its vanishing procyclicality of productivity cannot be determined easily. Moreover, evidence from all the other 8 countries essentially refutes the claim that changes in job separation rate is a significant determinant of changes in productivity correlations.
A.4 Evidence for De-unionization across U.S. States

The following two maps of mainland U.S. group 49 U.S. states (the states of Alaska and Hawaii are missing) into deciles, according to (i) the percentage change in unionization between the average union densities in the pre- and post-1984 periods (Figure A.3), and (ii) the change in correlation between employment growth and output per worker growth in the pre- and post-1984 periods (Figure A.4).

Figure A.3: De-unionization in U.S. States around 1984
Note: Lighter shades correspond to larger percentage of de-unionization.

Figure A.4: Vanishing Procyclicality of Labour Productivity in U.S. States around 1984
Note: Lighter shades correspond to larger decrease in labour productivity correlation.
Figure A.5: Cross-State Evidence for De-unionization

Note: Categorization of states into Right-to-Work and Non Right-to-Work has been done based on the status in 1984. Data on state-level unionization rates comes from the Current Population Survey (CPS), collected by Hirsch and Macpherson (2003). State-level data on real non-farm gross domestic product and total employment between 1969 and 2010 is sourced from the Bureau of Economic Analysis (BEA). Since hours worked data is not available at the state level, employment is used as the measure of labour input and labour productivity is defined as the state real non-farm gross domestic product per worker. I use annual growth rate as the filter because the preferred Baxter and King (1999) filter leads to 12 years of missing observations and leaves only 3 years of data before 1984. All changes in variables are calculated as the difference between the pre and post-1984 averages. Although observation for each state is weighted by its average employment in the regression, to improve readability I have not shown the weights here through bubbles, rather made it explicit in Figures A.3 and A.4. The p-value of the slope coefficient using robust standard error is reported in parentheses.
A.5 Evidence for De-unionization: A Difference-in-Difference Strategy

I will use sectoral variation across U.S. industries to see if de-unionization caused labour productivity correlation to fall. To argue for this causal channel, I follow a difference-in-difference regression strategy similar to Card (1992). I consider a very simple structural model that explains the fall in employment adjustment cost in industry $i$, $\Delta \text{Cost}_i$, as a function of the fraction of workers unionized in the industry prior to mid-1980s, $\text{Union}^\text{pre}_i$, and the change in correlation of labour productivity with hours worked, $\Delta \text{Corr} (\text{lp}_i, h_i)$, as a function of that change in cost:

$$\Delta \text{Cost}_i = a + b \text{Union}^\text{pre}_i + e_i$$  \hspace{1cm} (A.1)
$$\Delta \text{Corr} (\text{lp}_i, h_i) = \alpha + \beta \Delta \text{Cost}_i + \varepsilon_i$$  \hspace{1cm} (A.2)

The above system of structural equations can be combined to a reduced-form correlation change equation:

$$\Delta \text{Corr} (\text{lp}_i, h_i) = (\alpha + a\beta) + b\beta \text{Union}^\text{pre}_i + (\beta e_i + \varepsilon_i)$$

$$\Rightarrow \Delta \text{Corr} (\text{lp}_i, h_i) \equiv \beta_0 + \beta_1 \text{Union}^\text{pre}_i + \eta_i$$  \hspace{1cm} (A.3)

Figure A.6: Difference-in-Difference Effect of Union Density on Productivity Correlation

Note: Data on industry-level unionization rates comes from the Current Population Survey (CPS), collected by Hirsch and Macpherson (2003). Labour productivity is defined as real value added per hour worked. Data on value-added, hours and employment comes from KLEMS dataset. CPS industry codes for unionization and SIC industry codes for labour productivity were matched to create a consistent set of 17 U.S. industries. The BK bandpass filter between 2 and 8 years have been used to de-trend the variables. Change in productivity correlations is the difference in correlation between the post-1984 period (1984-2003) and the pre-1983 period (1964-1983). Since industry-level union data is available only from 1983 onwards, I have used the 2-year average of 1983 and 1984 values as the measure of pre-1984 level of union density. Size of the bubbles represent pre-1983 average industry employment level. The p-value of the slope coefficient using robust standard errors is reported in parentheses.

Equation (A.3) can be interpreted as showing the impact on productivity correlations in different industries which were differentially impacted by de-unionization. In other words, if one thinks of the fall in union rates around the early 1980s as the treatment, then the intensity of treatment varied...
across industries according to the pre-intervention level of union densities in those industries. In particular, an industry with a higher pre-intervention level of union density should be impacted more by the de-unionization treatment, thereby leading to a larger fall in productivity correlations. As an extreme example, an industry with no unionization to begin with will experience no impact of the de-unionization event. Running the regression in equation (A.3) across 17 U.S. industries, I find a significant positive effect of union density on the fall in productivity correlation, as shown in Figure A.6. In order to avoid small industries driving the correlation pattern, I weighted the observations by the pre-1983 average industry employment level.

Finally, replacing the change in productivity correlations by the change in the relative volatility of employment in equation (A.3), I find that industries with a larger pre-1984 level of union density experienced a larger increase (or a smaller decrease) in the volatility of employment relative to that of output and hours per worker. This is shown in Figure A.7.

![Figure A.7: Difference-in-Difference Effect of Union Density on Relative Volatility of Employment](image)

**Figure A.7: Difference-in-Difference Effect of Union Density on Relative Volatility of Employment**

*Note:* Data on industry-level unionization rates comes from the Current Population Survey (CPS), collected by Hirsch and Macpherson (2003). Labour productivity is defined as real value added per hour worked. Data on value-added, hours and employment comes from KLEMS dataset. CPS industry codes for unionization and SIC industry codes for labour productivity were matched to create a consistent set of 17 U.S. industries. The BK bandpass filter between 2 and 8 years have been used to de-trend the variables. Change in productivity correlations is the difference in correlation between the post-1984 period (1984-2003) and the pre-1983 period (1964-1983). Since industry-level union data is available only from 1983 onwards, I have used the 2-year average of 1983 and 1984 values as the measure of pre-1984 level of union density. Size of the bubbles represent pre-1983 average industry employment level. The p-value of the slope coefficient using robust standard errors is reported in parentheses.
A.6 Choice of SVAR Specification

The seminal paper of Galí (1999) showed that labour input responds negatively to technology shocks on impact. In Galí’s Vector Auto-Regression (VAR) specification, technology shocks were identified as the only shock that could change productivity in the long run. Since this finding was at odds with the standard wisdom of a real business cycle model where technology shocks are positively correlated with both output and hours input, a lot of criticism was generated against this finding.

The main criticism of Galí’s finding was that it was not robust to how the variables in the VAR, particularly the measure of labour input, were filtered. Christiano, Eichenbaum, and Vigfusson (2003) show that filtering the measure of labour inputs by taking its growth rate generates the spurious negative impulse response of per capita hours to a positive technology shock. They argue that per capita hours worked cannot be a non-stationary process, and hence differentiating an already stationary time series creates the spurious negative correlation. In fact, when per capita hours enters the SVAR in levels, instead of growth rates, technology shocks indeed become positively correlated with hours. Nevertheless, it has since been argued that not controlling for low-frequency movements in the labour input might introduce spurious correlations with productivity growth. A host of new VAR estimation techniques, like Threshold VAR by Ferraresi, Roventini, and Semmler (2016), and Bayesian estimation of Fractionally Integrated VAR by Doppelt and O’Hara (2018) — all corroborate that after controlling for low-frequency movements, hours per capita responds negatively to a technology shock on impact.

In this paper, I will use the technique in to control for the low-frequency movements in per capita hours worked, and use the same identifying assumption as in Galí (1999). Galí and Gambetti (2009) use a VAR model with time-varying coefficients and stochastic volatility of the innovations. Defining $x_t = [\Delta (y_t - n_t), n_t]$, where $y_t$ and $n_t$ denote the (log) output and (log) hours in per capita terms, the reduced form VAR can be written as:

$$x_t = A_{0,t} + A_{1,t} x_{t-1} + A_{2,t} x_{t-2} + \ldots + A_{p,t} x_{t-p} + u_t$$ (A.4)

where $A_{0,t}$ is a vector of time-varying intercepts, $A_{i,t}$, $i = 1, \ldots, p$ are matrices of time-varying coefficients, and the sequence of innovations $\{u_t\}$ follows a Gaussian white noise process (uncorrelated with all lages of $x_t$) with zero mean and time-varying covariance matrix. Crucially, the presence of a time-varying intercept in equation A.4 absorbs the low-frequency co-movement between productivity growth and per capita hours, thereby overcoming potential distortions in the VAR estimation. There are two main advantages of this specification: first, it allows one to control for low-frequency movements in per capita hours without having to extract the cyclical component of hours through any form of ad hoc time series filtering, and second, it allows one to know the complete dynamics of the impulse responses over the years so that it can be pin-pointed as to exactly when the responses began to change. Nonetheless, this method of controlling for the low-frequency movements in per capita

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37 In a two-variable SVAR with productivity growth and per capita hours, the identifying assumption implies that the long run coefficient matrix is lower triangular, that is, $\left(\begin{array}{c} \Delta (y_t - n_t) \\ n_t \\ \end{array} \right) = \left(\begin{array}{cc} C_{11}(L) & 0 \\ C_{21}(L) & C_{22}(L) \end{array} \right) \left(\begin{array}{c} \epsilon_t^a \\ \epsilon_t^\nu \end{array} \right)$, where $\epsilon_t^a$ is the technology shock, and $\epsilon_t^\nu$ is the non-technology or demand shock.

38 There were other criticisms as well. For example, Chang and Hong (2006) argue that TFP should be used instead of labour productivity as the measure of productivity in the VAR to properly identify technological shocks. I have compared the results obtained by using both these measures of productivity in the main paper in details. Chari, Kehoe, and McGrattan (2008) argue that the use of long run restrictions in structural VAR to identify shocks, like Galí’s identification argument, is not helpful for developing business cycle theories in general. However, Francis, Owyang, Rousch, and DiCecio (2014) provide a flexible finite-horizon alternative to the long run restrictions, and corroborate Galí’s conclusions.
hours also generates a negative response of hours to a positive technology shock, as discussed in the paper.

As an alternative to VAR specifications, which require strong identifying assumptions, I present an alternative methodology, à la Jorda (2005), of estimating the impulse response of hours to changes in utilization-adjusted TFP. For this projection-type analysis, I run the regression specification used by Ramey (2016):

\[
\ln \left( \frac{\text{hours}_t}{\text{pop}_t} \right) = \alpha_h + \beta_h \Delta \ln (\text{uatfp}_t) + \theta_h (L) X_{t-1} + \varepsilon_{t+h} \tag{A.5}
\]

\(\beta_h\): Response of hours at time \(t + h\) to a technology shock at time \(t\).
\(X_{t-1}\): One-period lagged values of growth rate of utilization-adjusted TFP, log per capita hours, log real GDP per capita, log labour productivity, and log real stock prices per capita.
\(\varepsilon_{t+h}\) is serially correlated, and so standard errors incorporate Newey-West correction.

![Figure A.8: IRF of Per Capita Hours to Utilization-Adjusted TFP Shock](image)

*Note:* The solid blue and red lines are the impulse responses of per capita hours to one percent rise in utilization-adjusted TFP in the pre-1983 and post-1984 periods respectively. The corresponding dashed and dotted lines are the 90 percent confidence intervals for the impulse responses. All data for the regression come from Ramey (2016).

This methodology of a simple regression model with the shock being the explanatory variable not only shows the negative correlation of hours and technology shock but also that the negative response of hours became muted after the mid-1980s (see Figure A.8.)
A.7 Impulse Response Functions from Time-Varying SVARs

![Graphs showing impulse responses to technology and demand shocks for hours, labor productivity, and output.](image)

Figure A.9: Dynamic Impulse Responses to Technology & Demand Shocks

**Note:** Impulse Response Functions (IRF’s) of per-capita hours, labour productivity and per-capita output from a 2-variable (viz., labour productivity growth and per-capita hours) time-varying long-run SVAR. Data is sourced from the BLS-LPC quarterly dataset for the U.S. business sector.
Figure A.10: Difference in Impulse Responses between Pre- & Post-1984

Note: Post-1984 impulse response minus pre-1984 impulse response of per-capita hours, labour productivity and per-capita output from a 2-variable (viz., labour productivity growth and per-capita hours) time-varying long-run SVAR. The solid line is the difference in the impulse responses between pre- and post-1984 periods. The dotted and dashed lines are the 95% and 90% confidence intervals of the difference respectively. Data is sourced from the BLS-LPC quarterly dataset for the U.S. business sector.
Figure A.11: Dynamic Impulse Responses to Technology & Demand Shocks

Note: Impulse Response Functions (IRF’s) of per-capita hours and TFP from a 2-variable (viz., TFP growth and per-capita hours) time-varying long-run SVAR. Hours data is sourced from the BLS-LPC quarterly dataset, TFP data is sourced from Fernald’s quarterly TFP series, and quarterly civilian non-institutional population (16 years of age and older residing in the 51 U.S. states, who are not inmates of institutions, e.g., penal and mental facilities, homes for the aged, etc.) data is from the Employment Situation release of the BLS. All data correspond to the U.S. business sector.
Figure A.12: Empirical Impulse Responses to Technology & Demand Shocks

Note: Impulse Response Functions (IRF) for the pre-1984 period (1956-1983) are in blue, and the post-1984 (1984-2017) IRF’s are in red dashed lines. Hours data is sourced from the BLS-LPC quarterly dataset, both types of TFP data are sourced from Fernald’s quarterly series, and quarterly civilian non-institutional population (16 years of age and older residing in the 51 U.S. states, who are not inmates of institutions, e.g., penal and mental facilities, homes for the aged, etc.) data is from the Employment Situation release of the BLS. All data correspond to the U.S. business sector.
Figure A.13: Difference in Impulse Responses between Pre- & Post-1984

Note: Post-1984 impulse response minus pre-1984 impulse response of per-capita hours and TFP from a 2-variable (viz., TFP growth and per-capita hours) time-varying long-run SVAR. The solid line is the difference in the impulse responses between pre- and post-1984 periods. The dotted and dashed lines are the 95% and 90% confidence intervals of the difference respectively. Hours data is sourced from the BLS-LPC quarterly dataset, TFP data is sourced from Fernald’s quarterly TFP series, and quarterly civilian non-institutional population (16 years of age and older residing in the 51 U.S. states, who are not inmates of institutions, e.g., penal and mental facilities, homes for the aged, etc.) data is from the Employment Situation release of the BLS. All data correspond to the U.S. business sector.
Figure A.14: **Conditional Volatility of Hours**

*Note*: Time-varying standard deviations of per capita hours, conditional on technology shock (blue dashed line) and demand shock (red dotted line). Measures of productivity are different in the two panels. Panels (a) and (b) use growth rates of labour productivity and TFP respectively, along with per capita hours as the two variables in the SVAR.

Figure A.15: **Conditional Volatility of Productivity**

*Note*: Time-varying standard deviations of productivity, conditional on technology shock (blue dashed line) and demand shock (red dotted line). Measures of productivity are different in the two panels. Panels (a) and (b) use growth rates of labour productivity and TFP respectively, along with per capita hours as the two variables in the SVAR.
A.8 Cyclical Moments of Capital and Factor Utilization

The model in this paper does not feature capital, rather includes only employment and effort. Since labour effort is not directly measurable in the data, one concern is that whatever is being labelled as ‘effort’ in the model is essentially capital, the missing factor of production. Therefore, it is important to distinguish between the business cycle dynamics of effort and capital. Using factor utilization rate as an empirically measurable proxy for effort, I show below how the cyclical moments of factor utilization in the data is qualitatively consistent with those of effort in the model, and they are different from those of capital.

![Figure A.16: Cyclical Correlations of Capital and Factor Utilization](image)

**Figure A.16: Cyclical Correlations of Capital and Factor Utilization**  
*Note:* Data on quarterly growth rates of capital input, factor utilization, output and hours worked for the U.S. business sector are sourced from Fernald (2014). A centred rolling window of 15 years is used to calculate the second moments. Findings are robust to alternative choice of filters and window-sizes.

Looking at panels (b) and (d) in Figure A.16, one can see that exactly around the time when productivity started losing its procyclicality, factor utilization also became more countercyclical. This fact was already presented in Table 2.1, where it was shown that the fall in aggregate TFP correlations with output and hours worked was driven by the reduced procyclicality of factor utilization and not utilization-adjusted TFP. However, it is immediately clear from the cyclical correlations of capital in panels (a) and (c) of Figure A.16 that capital became more procyclical around the mid-1980s unlike factor utilization. Now, if the model implied correlations of effort with output and employment matches with those of factor utilization in the data then it can be argued that the role played by
effort in the model is not the same as that of capital. Under the baseline calibration of the model (corresponding to column (4) of Table 4.3), correlation of effort with labour productivity fell by 0.37, which is qualitatively similar to that of factor utilization.

Figure A.17: Relative Volatility of Capital over the Business Cycle (1954-2010)

Note: Data on quarterly growth rates of capital input, factor utilization and output for the U.S. business sector are sourced from Fernald (2014). A centred rolling window of 15 years is used to calculate the second moments. Findings are robust to alternative choice of filters and window-sizes.

The volatility of capital relative to that of output and factor utilization rises sharply since the mid-1980s. It has already been shown that the relative volatility of employment has similarly rose. This further shows that the reliance on extensive margin of factor adjustment, for both labour and capital, has increased relative to the intensive margin of factor utilization. The model also predicts a substantial increase in the relative volatility of employment with respect to effort. All this evidence shows that the role of effort in the model is different from that of capital.
A.9 System of log-linearized equations

Log-linearizing the model around a zero-inflation ($\pi^p = 0$) steady state with unit effort ($\bar{E} = 1$), I get the following equations in log-deviation form, where the notation $\hat{x}_t$ is used to denote the deviation of logarithm of the variable $X_t$ from its logged steady state value $\bar{x}$.

\[ \begin{align*}
\hat{y}_t & = (1 - \Theta) \hat{c}_t + \Theta \left( \hat{h}_t + \hat{g}_t \right) \\
\hat{y}_t & = a_t + \hat{n}_t + \psi \hat{e}_t \\
\hat{n}_t & = (1 - \delta) \hat{n}_{t-1} + \delta \hat{h}_t \\
\hat{g}_t & = \gamma \hat{h}_t \\
\hat{\lambda}_t & = \hat{n}_t + \zeta \frac{(1 + \phi)}{1 + \zeta} \hat{e}_t \\
\hat{c}_t & = \mathbb{E}_t (\hat{c}_{t+1}) - \hat{\lambda}_t \\
\hat{\rho}_t & = \hat{n}_t - \mathbb{E}_t (\pi_{t+1}^w) \\
\hat{\pi}_t^w & = \beta \mathbb{E}_t (\pi_{t+1}^w) - \lambda_w \hat{\pi}_t^p \\
\hat{\pi}_t^p & = \beta \mathbb{E}_t (\pi_{t+1}^p) - \lambda_w \hat{\pi}_t^p \\
\hat{\pi}_t^r & = \left( \hat{y}_t - \hat{n}_t \right) - \left[ (1 - \Phi) \hat{\omega}_t + \Phi \hat{b}_t \right] \\
\hat{\lambda}_t & = \frac{1}{1 - \beta (1 - \delta)} \hat{y}_t - \frac{\beta (1 - \delta)}{1 - \beta (1 - \delta)} \left[ \mathbb{E}_t (\hat{y}_{t+1}) - \hat{\lambda}_t \right] \\
\bar{mrs}_t & = \kappa \left( \hat{c}_t + \varphi \hat{e}_t \right) + (1 - \kappa) \left[ (\hat{y}_t - \hat{n}_t - \hat{\pi}_t^p) + \frac{l}{1 - t} (\hat{\omega}_t + \hat{n}_t - \hat{c}_t) \right] \\
\hat{\omega}_t & = \hat{\omega}_{t-1} + \pi_{t}^w - \pi_{t}^p \\
\hat{\pi}_{t}^w & = \beta (1 - \delta) \mathbb{E}_t (\pi_{t+1}^w) - \lambda_w \left( \hat{\omega}_t - \omega_{t}^{\text{target}} \right) \\
\hat{\omega}_{t}^{\text{target}} & = \Upsilon \bar{mrs}_t + (1 - \Upsilon) \left( \hat{y}_t - \hat{n}_t - \hat{\pi}_t^p \right) \\
\hat{\pi}_{t} & = \rho \hat{\pi}_{t-1} + (1 - \rho) \left( \phi_x \hat{\pi}_{t} + \phi_y \hat{y}_t \right) + \phi \Delta \hat{y}_t + \nu_t \\
\hat{\lambda}_t & = \frac{1}{1 + \phi} \left( \hat{y}_t - \hat{n}_t - \hat{\pi}_t^p - \hat{c}_t - \varphi \hat{\lambda}_t \right) \\
\nu_t & = \rho_\nu \nu_{t-1} + \varepsilon_t
\end{align*} \]

where $\Theta = \frac{\Gamma(\delta \kappa) Y^{1+\gamma}}{\gamma}$, $\Phi = \frac{B}{B + W}$, $\kappa = \left( \frac{\chi}{1 + \zeta} \right) \left( \frac{C}{MRS} \right)$, $\lambda_w = \frac{(1 - \theta_w)(1 - \beta \theta_w (1 - \Theta))}{\theta_w [1 - (1 - \Upsilon)(1 - \Phi)]}$, and $\hat{\omega}_t = \hat{w}_t - \hat{\rho}_t$. 

63
A.10 Volatility of Monetary Policy Shock

Figure A.18: 5-Year Rolling Standard Deviation of Romer-Romer Monetary Shock

Note: Ignoring the sudden jump in volatility in the monetary policy shock between 1977 and 1982 as seen in Panel (a), the average standard deviation in the 1984-2005 period is roughly half of the average standard deviation during 1971-1977, as shown in Panel (b).
A.11 Model: Robustness Checks

A.11.1 Convexity of Hiring Cost Function

The hiring cost function is taken to be quadratic in the baseline calibration of the model. However, there is no agreement in the literature as to the degree of convexity of the function.

<table>
<thead>
<tr>
<th>Business Cycle Moments</th>
<th>Changes in Moments</th>
<th>γ = 0.6</th>
<th>Baseline, γ = 1</th>
<th>γ = 2.4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
<tr>
<td>Labour Productivity Correlations</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output: $\text{Corr} (y_t, lp_t)$</td>
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<td>-0.40</td>
<td>-0.46</td>
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<tr>
<td>Employment: $\text{Corr} (n_t, lp_t)$</td>
<td></td>
<td>-0.34</td>
<td>-0.39</td>
<td>-0.35</td>
</tr>
<tr>
<td>Hiring Flows: $\text{Corr} (h_t, lp_t)$</td>
<td></td>
<td>-0.48</td>
<td>-0.47</td>
<td>-0.33</td>
</tr>
<tr>
<td>Relative Volatility of Employment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output: $s.d. (n_t) / s.d. (y_t)$</td>
<td></td>
<td>+19%</td>
<td>+27%</td>
<td>+48%</td>
</tr>
<tr>
<td>Conditional $\text{Corr} (n_t, lp_t)$</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology Shock</td>
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<td>-0.07</td>
<td>-0.05</td>
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<tr>
<td>Demand Shock</td>
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<td>-0.71</td>
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<tr>
<td>Conditional $\text{Corr} (y_t, lp_t)$</td>
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<td></td>
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<tr>
<td>Technology Shock</td>
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<td>-0.07</td>
<td>-0.08</td>
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<tr>
<td>Demand Shock</td>
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<td>-0.44</td>
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<td>Real Wage Correlations</td>
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<tr>
<td>Output: $\text{Corr} (y_t, w_t)$</td>
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<td>-0.03</td>
<td>-0.11</td>
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</table>

**Note:** Columns (1) through (3) report changes in business cycle moments between pre and post-1984 periods for alternative values of parameter, $\gamma$, denoting the degree of convexity of the hiring cost function. All other parameters in the model are fixed at the calibration values used in column (4) of Table 4.3, which corresponds to the total effect of de-unionization. To maintain comparability with the existing literature, all moments have been calculated on quarterly Hodrick-Prescott-filtered variables.

Mortensen and Nagypál (2007) find that in the presence of search frictions with linear vacancy posting costs, the matching function has an unemployment elasticity of 0.6. Interpreting employment adjustment costs as search frictions, a natural calibration for $\gamma$ in the current model is therefore 0.6. On the other hand, Merz and Yashiv (2007) directly estimate the convexity of the average employment adjustment cost, and reports a value of 2.4. In Table A.5 I show the robustness of the quantitative model predictions for different values of $\gamma$ in this range.
### A.11.2 Increasing Marginal Disutility from Effort

In the baseline calibration of the model, the degree of increasing marginal disutility from exerting more effort, $\phi$ is taken to be 1.5. Since there is no consensus in the literature regarding this value, in Table A.6 I show the robustness of the model’s quantitative performance for alternative values of $\phi$.

<table>
<thead>
<tr>
<th>Business Cycle Moments</th>
<th>Changes in Moments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\phi = 0.5$</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>Labour Productivity Correlations</strong></td>
<td></td>
</tr>
<tr>
<td>Output: $\text{Corr}(y_t, l_{pt})$</td>
<td>-0.52</td>
</tr>
<tr>
<td>Employment: $\text{Corr}(n_t, l_{pt})$</td>
<td>-0.45</td>
</tr>
<tr>
<td>Hiring Flows: $\text{Corr}(h_t, l_{pt})$</td>
<td>-0.48</td>
</tr>
<tr>
<td><strong>Relative Volatility of Employment</strong></td>
<td></td>
</tr>
<tr>
<td>Output: $s.d.(n_t) / s.d.(y_t)$</td>
<td>+35%</td>
</tr>
<tr>
<td><strong>Conditional $\text{Corr}(n_t, l_{pt})$</strong></td>
<td></td>
</tr>
<tr>
<td>Technology Shock</td>
<td>-0.06</td>
</tr>
<tr>
<td>Demand Shock</td>
<td>-0.70</td>
</tr>
<tr>
<td><strong>Conditional $\text{Corr}(y_t, l_{pt})$</strong></td>
<td></td>
</tr>
<tr>
<td>Technology Shock</td>
<td>-0.07</td>
</tr>
<tr>
<td>Demand Shock</td>
<td>-0.86</td>
</tr>
<tr>
<td><strong>Real Wage Correlations</strong></td>
<td></td>
</tr>
<tr>
<td>Output: $\text{Corr}(y_t, w_t)$</td>
<td>-0.09</td>
</tr>
<tr>
<td>Employment: $\text{Corr}(n_t, w_t)$</td>
<td>-0.20</td>
</tr>
<tr>
<td>Labour Productivity: $\text{Corr}(l_{pt}, w_t)$</td>
<td>-0.10</td>
</tr>
</tbody>
</table>

**Note:** Columns (1) through (3) report changes in business cycle moments between pre and post-1984 periods for alternative values of parameter, $\phi$, denoting the degree of increasing marginal disutility from exerting more effort. All other parameters in the model are fixed at the calibration values used in column (4) of Table 4.3, which corresponds to the total effect of de-unionization. To maintain comparability with the existing literature, all moments have been calculated on quarterly Hodrick-Prescott-filtered variables.
A.12 Data on Intellectual Property Products

I use the current-cost net capital stock of private non-residential fixed assets published by the Bureau of Economic Analysis (BEA) at the industry-level from 1947 through 2016. The data is disaggregated by asset type according to the classification by the National Income and Product Accounts (NIPA) — there are three major categories, namely, (i) equipment, with 39 sub-types, (ii) structures, with 32 sub-types, and (iii) intellectual property products (IPP), with 25 sub-types. The BEA typically does not include detailed estimates of different types of capital assets by industry in the tables published in the Survey of Current Business or the Fixed Assets and Consumer Durables volume because their quality is significantly less than that of the higher level aggregates in which they are included. Compared to these aggregates, the detailed estimates are more likely to be either based on judgemental trends, on trends in the higher level aggregate, or on less reliable source data. Keeping this issue of data quality in mind, I will only use the share of aggregate IPP in total asset stock at the level of 24 U.S. industries. Below I present the time trend of the share of IPP in the total non-residential capital stock at current prices for the aggregate U.S. economy.

![Figure A.19: Share of IPP in Total Non-Residential Capital Stock in the U.S. (1960-2016)](image)

In order to give a clearer picture of what are the assets included under IPP, I provide below the complete list of NIPA asset-types that are categorized under IPP capital —

A. **Software**: Prepackaged, custom, and own account software

B. **Research & Development**: Pharmaceutical and medicine, other chemicals, semiconductor and other components, computers and peripheral equipment, communications equipment, navigational and other instruments, other computer and electronics, motor vehicles and parts, aerospace products and parts, and other manufacturing, scientific R&D services, software publishers, financial and real estate services, computer systems design and related services, all other non-manufacturing, private universities and colleges, and other non-profit institutions.

C. **Artistic Originals**: Theatrical movies, long-lived television programs, books, music, and other entertainment originals.
A.13 Relative Importance of Sector-Specific Shocks

Model:
\[ X_{i,t} = \lambda_i F_t + \varepsilon_{i,t} \]

- \( X_{i,t} \): Observed growth rate of value added output or labour input for sector \( i \) at time \( t \)
- \( F_t \): Principal component of sectoral growth rates common to all sectors at time \( t \)
- \( \varepsilon_{i,t} \): Sector-specific growth rate for sector \( i \) at time \( t \)

Estimation:
Variance-covariance matrix of \( X_{i,t} \), \( V \equiv \Gamma \Lambda \Gamma' \) (Eigenvalue-Eigenvector Decomposition)
\[ F_t = X_{i,t} \Gamma_1, \text{ where } \Gamma_1 \text{ is the first eigenvector in } \Gamma \text{ whose columns are sorted according to the ordering of the eigenvalues in } \Lambda. \]
The variance of \( F_t \) is interpreted as the aggregate economy-wide volatility (indicated as ‘Common’ in Tables A.7 and A.8), while that of \( \varepsilon_{i,t} \) is the ‘Sectoral’ variance.

Table A.7: Components of Variance of Value Added Output Growth

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Pre-1983</th>
<th>Post-1984</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Common</td>
<td>Sectoral</td>
</tr>
<tr>
<td>BEA: 13 Sectors</td>
<td>92.93%</td>
<td>7.07%</td>
</tr>
<tr>
<td>KLEMS: 10 Sectors</td>
<td>48.14%</td>
<td>51.86%</td>
</tr>
<tr>
<td>KLEMS: 31 Sectors</td>
<td>17.96%</td>
<td>82.04%</td>
</tr>
<tr>
<td>IIP: 8 Sectors</td>
<td>94.98%</td>
<td>5.02%</td>
</tr>
<tr>
<td>IIP: 12 Sectors</td>
<td>70.89%</td>
<td>29.11%</td>
</tr>
<tr>
<td>IIP: 20 Sectors</td>
<td>30.63%</td>
<td>69.37%</td>
</tr>
</tbody>
</table>

Table A.8: Components of Variance of Labour Input Growth

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Pre-1983</th>
<th>Post-1984</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Common</td>
<td>Sectoral</td>
</tr>
<tr>
<td>CES: 14 Sectors</td>
<td>68.64%</td>
<td>31.36%</td>
</tr>
<tr>
<td>BEA: 13 Sectors</td>
<td>92.31%</td>
<td>7.69%</td>
</tr>
<tr>
<td>KLEMS: 10 Sectors</td>
<td>78.28%</td>
<td>21.72%</td>
</tr>
<tr>
<td>KLEMS: 31 Sectors</td>
<td>89.36%</td>
<td>10.64%</td>
</tr>
</tbody>
</table>

It should be noted that most of the rise in the relative importance of sector-specific variance was due to the drop in the variance of the common component, while the sectoral component remained largely constant between the pre and post-1984 periods. In other words, one can conclude that the drop in variance of output and labour inputs during the Great Moderation was mostly due to falling volatility of the aggregate shocks rather than sectoral ones. However, this is not true when a 31-industry-split is considered — both the common and sectoral variances decline in that case.