The Productivity Puzzle and the Decline of Unions

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Abstract

This paper finds that rapid de-unionization can explain the sudden vanishing of the procyclicality of productivity in the U.S. during the 1980s. Cross-sectional evidence from U.S. states and industries shows that a lower cost of hiring and firing workers due to the decline in union power prompted firms to rely less on labour hoarding, making productivity less procyclical. In a model with endogenous worker effort, allowing the employment adjustment cost to fall by the amount implied by the decline in union density can generate more than half of the observed drop in the procyclicality of productivity.

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

JEL Codes: E22, E23, E24, E32, J50

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1 Introduction

A defining feature of the post-War U.S. economy has been the co-movement of productivity with output and labour along the business cycle. However, since the early 1980s, the procyclicality of productivity has vanished, resulting in a *productivity puzzle*, first brought to light by Stiroh (2009). Average labour productivity is now acyclical with output and countercyclical with hours worked. A substantial literature has explored a wide range of possible causes behind the sudden change in the business cycle dynamics of productivity.[1] One key explanation is the decline in hiring and firing frictions in the labour market, explored by Gordon (2010) and Galí and van Rens (2021). The idea is that the pre-1980 procyclicality of productivity was driven by *labour hoarding*, whereby firms, faced with costly hiring and firing of workers, chose to vary labour effort procyclically instead of adjusting employment. Since such changes in the intensity of labour utilization could not be observed in the changes in employment or hours worked, the measured productivity appeared to be procyclical.[2] Hence, it is natural to explain the vanishing procyclicality of productivity in the 1980s through a lower incidence of labour hoarding due to a decline in employment adjustment cost.

This paper is the first to show that de-unionization in the 1980s lowered the prevalence of labour hoarding, leading to the vanishing procyclicality of productivity. I develop the empirical argument for de-unionization as the explanation for the productivity puzzle in two steps. First, I show that there was a decline in employment adjustment costs around the mid-1980s in the U.S., simultaneous to the productivity puzzle. Second, I consider many possible reasons for the decline in hiring and firing costs and show that the strongest evidence exists for the de-unionization channel in terms of the timing and speed of change and the cross-sectional variation across U.S. states and industries.

Employment adjustment costs are not directly observed in aggregate data. Therefore, I have to use various proxies to provide evidence for a decline in employment adjustment costs. First, I show that the vanishing procyclicality of total factor productivity (TFP) in the mid-1980s was entirely driven by the reduced volatility of the procyclical factor utilization component of TFP, implying a lower prevalence of factor hoarding. Second, a sharp rise in the relative volatility of employment — a measure of the ease of employment adjustment, coincides with the reduction in procyclicality of productivity in terms of timing and cross-sectional variation among U.S. states and industries. Third, a time-varying SVAR analysis à la Galí and Gambetti (2009) reveals a stark reduction in procyclicality of productivity *conditional* on a demand shock, suggesting that in the post-1980 period firms have

[1] Different potential explanations have been suggested in the literature, namely, greater labour market flexibility (see Gordon (2010), Barnichon (2010) and Galí and van Rens (2021)), increased role of sector-specific shocks vis-à-vis aggregate economy-wide shocks (see Garin, Pries and Sims (2018) and vom Lehn and Winberry (2022)), enhanced importance of technology shocks relative to demand shocks (see Barnichon (2010)), more widespread use of intangible capital (see McGrattan and Prescott (2012)), greater incidence of performance pay (see Nucci and Riggi (2013)), more selective firing of low-productivity workers during recessions (see Berger (2016)), mortgage market deregulation (see Andrés, Boscá and Ferri (2013)), changes in inventory behaviour (see Sarte, Schwartzman and Lubik (2015)), and increases in unemployment insurance duration (see Rujiwattanapong (2022)).

[2] Biddle (2014) notes that labour hoarding as a concept dates back to Okun (1962) and Oi (1962). Direct empirical evidence for labour hoarding was provided in works such as Fay and Medoff (1985).

been meeting higher cyclical demand through additional hiring of workers instead of increasing the effort of existing workers.

While the above evidence suggests a sudden drop in employment adjustment cost in the 1980s, the question remains as to what structural change caused it. Some of the common channels of labour market flexibility, like an increase in part-time and temporary employment and the advent of online job search platforms, do not align well with the productivity puzzle regarding timing and speed. However, the rapid and sudden de-unionization episode of the early 1980s does. Between 1980 and 1985, there was a 33% decline in union density, a 50% decrease in union elections, and a 90% drop in the number of large-scale strikes. Using data going back to the late-1930s, I find a long-run relationship between union density and the cyclicality of productivity in the U.S. Union density and the procyclicality of productivity rose rapidly together before the 1950s, and they both started falling simultaneously in the 1980s after remaining high for three decades. Unions have often been linked to long-run trends like inequality (see Farber et al. (2021) for a recent example), but they have seldom been connected to business cycle dynamics like in this work.

In the U.S., about 90% of the de-unionization happened within states and industries and not through employment shifts towards less unionized sectors and regions. I show that industries and states that experienced a larger decline in union density also had a more pronounced increase in the ease of employment adjustment and a bigger drop in the procyclicality of productivity. The effect of de-unionization is shown to be concentrated among the U.S. states without right-to-work laws, which are designed to render unions less relevant for employment protection. Finally, I show that U.S. industries with higher union density have lower hiring and job separation rates. All this evidence implies that de-unionization can explain the productivity puzzle through the channel of a decline in employment adjustment cost.

Going beyond the U.S., I show that across 13 OECD countries, a de-unionization episode is strongly predictive of a decline in productivity procyclicality. Countries like Canada and Sweden did not undergo either de-unionization or a decline in productivity procyclicality. At the same time, the political climate of deregulation under the Reagan and Thatcher administrations led to a sharp decline in union power in the U.S. and the U.K., accompanied by more countercyclical productivity. The fact that union power did not decline in some advanced countries makes common international factors like skill-biased technological change unlikely explanations for the rapid de-unionization episode in the U.S.

To ascertain the quantitative relevance of the de-unionization channel for explaining the productivity puzzle, I use a general equilibrium framework with endogenous labour effort and costly employment adjustment. I find that allowing the employment adjustment cost in the model to fall by the amount implied by the decline in union density can match more than 60% of the drop in cyclical productivity correlation with output and more than half of the drop in correlation with total hours worked. While the decline in employment adjustment cost can match the changes in unconditional productivity correlations like Galí and van Rens (2021), my model with nominal rigidities can also match changes in productivity correlations conditional on technology and demand shocks.[3] Estimating a time-varying employment adjustment cost parameter to match the empirical and model-implied values of the relative volatility of employment for every year between 1954 and 2008, I show that the model matches not merely the change in productivity correlations between the pre and post-1984 periods but also the entire cyclical dynamics of productivity for more than half a century. Further, the model suggests that the reduction in the volatilities of technology and demand shocks during the Great Moderation, the more hawkish monetary policy under Volcker, and the increased nominal rigidities have all played, at best, a minimal role in explaining the productivity puzzle.

Finally, I empirically test the validity of other theoretical explanations for the productivity puzzle proposed in the literature. I do not find convincing evidence for a more selective firing of low-productivity workers during recessions (see Berger (2016)), the rise of services, the increased productivity-boosting inter-sectoral factor reallocation during recessions (see Garin, Pries and Sims (2018)), or the increased use of intangible capital (see McGrattan and Prescott (2012)) to have significantly contributed to the productivity puzzle.

The rest of the paper is structured as follows. Section 2 provides empirical evidence for greater labour market flexibility due to a decline in union power as an explanation for the productivity puzzle. Section 3 describes a dynamic stochastic general equilibrium model, whose performance in matching the empirical changes in the business cycle moments is quantified in Section 4. Section 5 discusses the lack of empirical evidence for a host of plausible explanations for the productivity puzzle. Section 6 summarizes the key conclusions.

2 Explaining the Productivity Puzzle: Empirical Evidence

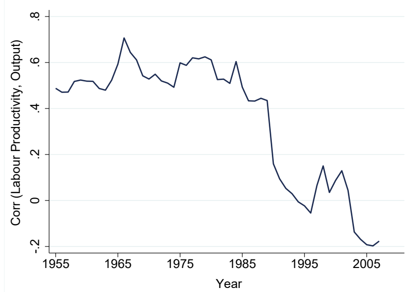
2.1 The Productivity Puzzle

The *productivity puzzle* refers to the sudden vanishing of procyclicality of productivity around the mid-1980s in the U.S.[4] Panels (a) and (b) of Figure 2.1 show the sudden and significant drop in the business cycle correlations of average labour productivity (ALP, defined as output per hour worked) with output and total hours worked. While I have used the Baxter and King (1999) (henceforth BK) bandpass filter to extract the cyclical component of the variables in Figure 2.1, the finding is robust to the choice of the de-trending method: quarterly and annual growth rates, and the Hodrick and Prescott (1997) (henceforth HP) filter. Findings are also robust to using quarterly data for the non-farm business sector, using annual KLEMS data for the aggregate U.S. economy, using employment

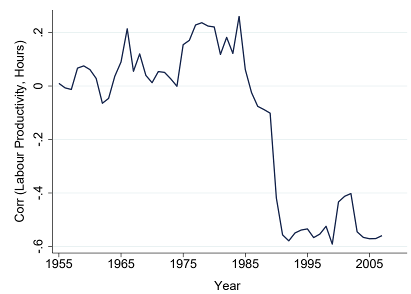
[3] Galí and van Rens (2021) use a modified real business cycle (RBC) model, which argues that the procyclicality of productivity emanates from procyclical technology shocks. However, the evidence of a negative response of employment to a positive technology shock in the SVAR analysis in Section 2.2.3 militates against the RBC paradigm.

[4] The term 'productivity puzzle' has been used in the literature to mean a variety of phenomena, e.g., the slow growth of productivity in recent years, the divergence between labour productivity and real wage growth, etc. However, following McGrattan and Prescott (2012), I use the term to refer to the drop in the contemporaneous correlations of the productivity with both output and labour input at business cycle frequencies. For a discussion on changes in non-contemporaneous productivity correlations with output and labour input, see Brault and Khan (2020).

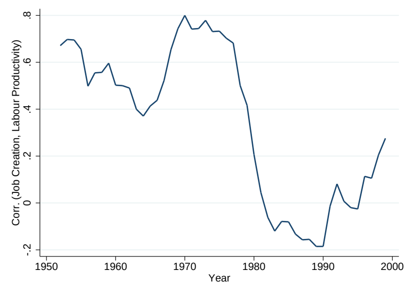
instead of total hours worked as the measure of labour input (Appendix A.1), and using TFP instead of ALP as the measure of productivity (Appendix A.2).[5]



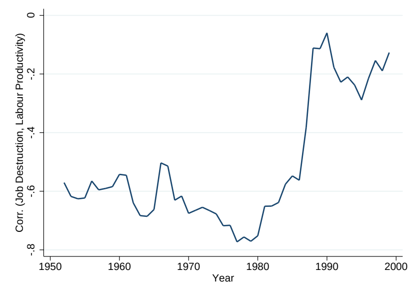
(a) Corr (ALP, Output)



(b) Corr (ALP, Hours)



(c) Corr (ALP, Job Creation)



(d) Corr (ALP, Job Destruction)

Figure 2.1: Vanishing Procyclicality of Productivity in the United States

Note: Output, hours and average labour productivity (output per hour worked) data for panels (a) and (b) are sourced from the *Labor Productivity and Costs* quarterly dataset published by the *Bureau of Labor Statistics* for the U.S. business sector. Data for panels (c) and (d) correspond to the U.S. manufacturing sector, sourced from Davis, Faberman and Haltiwanger (2006). Using the Help Wanted Index from the *Job Openings and Labor Turnover Survey* instead of the manufacturing job creation series in panel (c) yields similar dynamics of productivity correlations (not shown). The BK bandpass filter between 6 and 32 quarters is used to filter all the variables. Centred rolling windows of 15 and 10 years are used to calculate the correlations in panels (a)-(b) and (c)-(d), respectively. Findings are robust to alternative choices of filters and window sizes.

Since employment changes are composed of an inflow of workers through job creation or vacancies, and an outflow through job separations, it is natural to expect that the job creation rate should become more countercyclical, and/or the job separation rate should become more procyclical with productivity after the 1980s. Using data on job flows in the manufacturing sector, I corroborate these conjectures in panels (c) and (d) of Figure 2.1. All these pieces of evidence establish that the productivity puzzle is not an artefact of a particular dataset, or a specific statistical filtering process, or the choice of the measure of productivity or labour input.

The vanishing procyclicality of productivity since the mid-1980s has been related to jobless recoveries since the early 1990s (see Berger (2016) and Garin, Pries and Sims (2018)). However, the two phenomena are partially at odds with each other. While jobless recovery is consistent with the

[5]TFP has remained procyclical even after the drop, but ALP has become countercyclical with hours worked, and acyclical with output. The current paper is not concerned with these level differences but with the sudden drop in the cyclical productivity correlations around the mid-1980s. Hagedorn and Manovskii (2011) find that using labour data from the Current Population Survey (CPS) instead of the LPC data changes the levels of the cyclical productivity correlations, but the drop in the correlations in the mid-1980s remains unchanged.

declining correlation of productivity with labour input, it is inconsistent with the falling correlation of productivity with output. This is because, notwithstanding the stagnation in employment, jobless recoveries are characterized by a post-recession increase in both output and productivity, implying a continued high correlation between output and productivity, contrary to the productivity puzzle. Therefore, this paper will focus exclusively on the structural changes that can potentially explain the productivity puzzle and not necessarily the phenomenon of jobless recoveries.

2.2 Explaining the Puzzle: A Drop in Employment Adjustment Cost

Procyclicality of productivity has traditionally been 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 costs. Since hiring and firing costs are not directly observed as an aggregate time series, I use various proxies for such costs to show the decline in employment adjustment costs in the U.S. from the mid-1980s.

2.2.1 The Reduced Volatility of Factor Utilization Rate

Commonly used measures of productivity, like ALP and TFP, contain an implicit component of factor utilization rate that can itself have cyclical correlations with output and labour input. If factor utilization is higher during booms than during recessions, then measured productivity will be more procyclical. To illustrate, consider a production function with effective labour input, $Y = AE^{\alpha_1}N^{\alpha_2}$, where Y is the value-added, E is effort or utilization rate of each worker N, and A is the utilization-adjusted productivity component. ALP, defined as output per worker, $Y/N = AE^{\alpha_1}N^{\alpha_2-1}$, is increasing in E but decreasing in N for $\alpha_1 > 0$ and $\alpha_2 < 1$. Firms can change their effective labour input along the business cycle by changing E and/or N. When it is costly to adjust employment, firms mostly change E, making ALP procyclical. With lower employment adjustment costs, firms change N more, which being negatively correlated with ALP, leads to more countercyclical productivity.

Table 2.1: Business Cycle Moments of Components of TFP

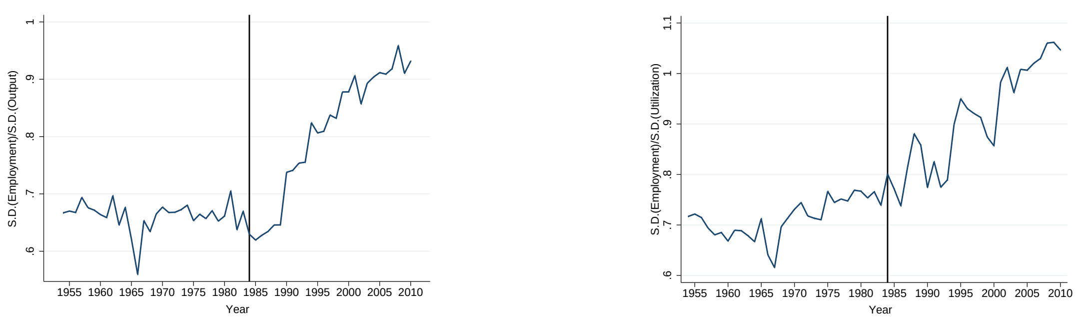
	Correlation with Output			Correlation with Hours			Variance	
Components of TFP	Pre-1983	Post-1984	Change	Pre-1983	Post-1984	Change	Pre-1983	Post-1984
TFP	0.90	0.71	-0.18†	0.45	-0.06	-0.51*	14.23 (100%)	5.91 (100%)
Factor Utilization	0.72	0.41	-0.31†	0.72	0.44	-0.28†	8.38 (58.9%)	0.97 (16.4%)
Utilization-Adjusted TFP	0.14	0.32	+0.18$^{\#}$	-0.33	-0.37	-0.04^{o}	5.85 (41.1%)	4.94 (83.6%)

Note: Data on quarterly growth rates of all the variables for the U.S. business sector are sourced from Fernald (2014). Fernald (2014) provides data only in growth rates, and results are robust to using annual instead of quarterly growth rates. See Appendix A.2 for a discussion on robustness to alternative de-trending methods using the version of Fernald (2014) data as compiled by Ramey (2016). Pre-1983 and post-1984 periods refer to the following two 20-year periods: 1964 through 1983, and 1984 through 2003, respectively. Using data for the period before 2007 bypasses some of the issues arising from the revision of Fernald (2014) data, as pointed out by Kurmann and Sims (2021). †, * and $^{\#}$ denote statistical significance at 1%, 5% and 10% levels respectively, while ^{o} means that the change is statistically indistinguishable from zero. Standard errors are calculated using the delta method. Results are robust to using employment instead of total hours worked. The covariance term between factor utilization rate and utilization-adjusted TFP is equally split while calculating the variances of the two components of TFP. Percentages in parentheses refer to the share of total variance of TFP that is explained by each component. Appendix Table A.4 shows that the cyclical dynamics of factor utilization are similar to those of the capacity utilization rate based on the Quarterly Survey of Plant Capacity (QSPC) by the Census Bureau.

Using hours per worker as a proxy proportional to unobserved changes in both labour effort and capital utilization, Basu, Fernald and Kimball (2006) generate a series for the intensive margin of factor use, and a TFP series adjusted for such factor utilization (see Appendix A.2). Table 2.1 shows that utilization-adjusted TFP has historically been and continues to be much less procyclical than factor utilization. Hence, in a variance decomposition sense, if the relative contribution of factor utilization rate falls in the total variability of aggregate TFP, the latter will become more countercyclical. The right panel of Table 2.1 shows that the share of total variation of TFP explained by the more procyclical component of factor utilization rate has indeed diminished sharply in the post-1984 period (from 59% to 16% of the total cyclical variance of TFP), pointing towards a drop in the relative cost of factor adjustment along the extensive margin, namely, hiring and firing in the labour market.

2.2.2 The Rising Relative Volatility of Employment

If firms rely more on hiring and firing rather than changes in the intensive margin of worker effort, falling employment adjustment costs should raise the volatility of employment relative to those of output and factor utilization. Figure 2.2 shows the dramatic rise in the volatility of employment (the extensive margin of labour) relative to that of output and the intensive margin of factor utilization exactly at the time of the sudden drop in the productivity correlations. Appendix Table A.2 shows that even though the absolute volatilities of both output and employment declined unanimously from the late 1970s during the Great Moderation, the magnitude of reduction was larger for output than for employment, leading to the increase in the relative volatility of employment.

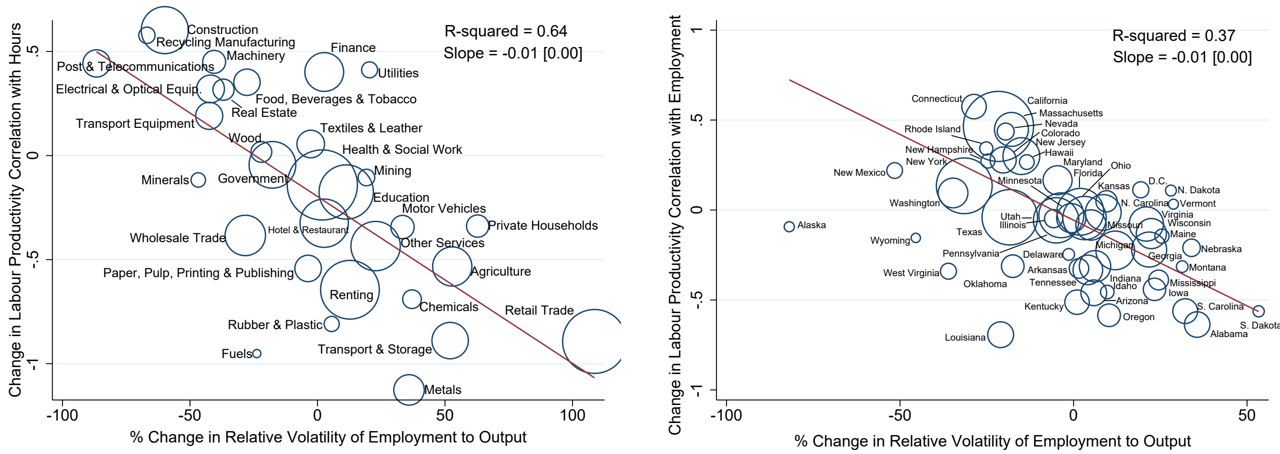


(a) $\frac{\text{s.d.(Employment)}}{\text{s.d.(Output)}}$ (b) $\frac{\text{s.d.(Employment)}}{\text{s.d.(Utilization)}}$

Figure 2.2: Relative Volatility of Employment over the Business Cycle (1954-2010)

Note: Data for employment and output is sourced from the BLS-LPC quarterly dataset for the U.S. business sector. The Christiano and Fitzgerald (2003) band-pass filter between 6 and 32 quarters have been used to extract the cyclical component of the variables in panel (a) since the BK filter (used for correlation analysis) distorts the amplitude of the extracted cycle. Annualized quarterly growth rate has been used in panel (b) since data on factor utilization from Fernald (2014) is only available in growth rates. A centred rolling window of 15 years is used to calculate the second moments. The vertical lines are at 1984, denoting the year from which productivity started to lose its procyclicality. Findings are robust to alternative choices of filters and window sizes.

Not only the timing but also the cross-sectional distribution of the rise in relative volatility of employment matches with the fall in productivity correlations across U.S. industries and states. In Figure 2.3, I show that the percentage change in volatility of employment relative to that of output between pre and post-1984 has a statistically significant negative correlation with the change in labour productivity correlation with total labour input across 31 U.S. industries and 51 U.S. states. Galí and van Rens (2021) found a similar result across 3-digit U.S. industries for changes in business cycle moments around 1999. In a related context, Llosa et al. (2014) and Dossche, Gazzani and Lewis (2023) also establish a negative correlation between the level of procyclicality of productivity and the level of relative volatility of employment across OECD countries. All of them use these findings to motivate the link between labour market flexibility and procyclicality of productivity, but stop short of explaining what could have caused sudden changes in that flexibility for the U.S. This is the gap in the literature that I aim to fill in Section 2.3 below.



(a) 31 U.S. Industries

(b) 51 U.S. States

Figure 2.3: Vanishing Procyclicality of Productivity & Rising Relative Volatility of Employment

Note: All changes are between the post and pre-1984 periods. Observations are weighted by the average employment level in each industry or state, denoted by the size of the bubbles. The p-value of the slope coefficients using robust standard errors are reported in parentheses. (a) Annual industry-level data, classified by SIC, on value added, hours and employment between 1947 and 2010 comes from KLEMS dataset, collected by Jorgenson, Ho and Samuels (2012). Labour productivity is defined as real value added per hour worked. The BK band-pass filter between 2 and 8 years have been used to de-trend the variables. (b) Annual state-level data on real non-farm gross domestic product and total employment between 1969 and 2010 is sourced from the BEA. Labour productivity is defined as the state real non-farm gross domestic product per worker, since hours worked data is not available at the state level. I use annual growth rate to de-trend the variables because the preferred BK band-pass filter leaves only 3 years of data before 1984. Factor utilization data is not available at either the industry or state level to replicate the analysis using the relative volatility of employment vis-à-vis the intensive margin of factor utilization.

2.2.3 Changes in Response to Technology and Demand Shocks

Structural changes that make hiring and firing of workers easier for firms affect how the economy responds to different types of shock (see Van Zandweghe (2010)). For example, faced with a positive demand shock, when the hiring cost is low, firms can meet the extra demand by hiring more workers instead of making their available workers put in more effort. This would imply a muted rise in labour productivity in response to a positive demand shock after the 1980s when employment adjustment costs arguably decreased. To test the empirical validity of this conjecture, I study the changes in the correlations of productivity and labour input conditional on demand and technology shocks between

1950 and 2017. Following Galí and Gambetti (2009), I run a time-varying structural vector autoregression (SVAR) with two variables: ALP growth and per capita hours worked. The technology shock is identified as the innovation that affects productivity growth in the long run (see Galí (1999)), while the remaining disturbance is called the demand shock.[6] I find a sudden and massive reduction in the correlation between labour input and productivity conditional on a demand shock around the mid-1980s (see the red dotted line in Figure 2.4). This corroborates the narrative of structural changes in the labour market, making it more flexible in the post-1980 period.

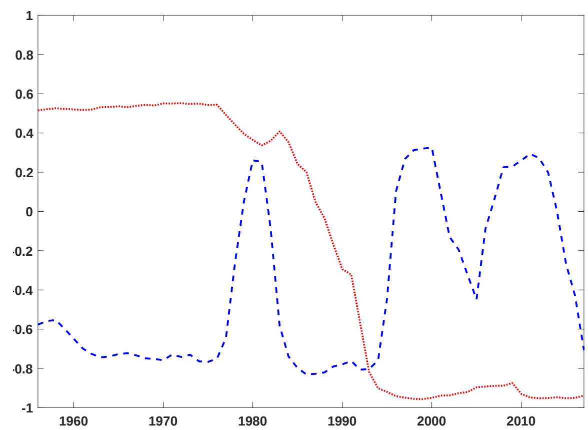


Figure 2.4: Correlations of Productivity with Hours Conditional on Technology and Demand Shocks
Note: Time-varying correlations of per capita hours with average labour productivity, conditional on technology shock (blue dashed line) and demand shock (red dotted line).

Technology shocks induced a negative correlation between per capita hours and labour productivity for most years before the mid-1980s (see the blue dashed line in Figure 2.4).[7] Barnichon (2010) used this finding to argue that increased importance of technology shock relative to demand shock in the post-1980 era can make productivity more countercyclical with labour input. However, conditional on a technology shock, productivity has always been procyclical with output. So the increasing importance of technology shocks cannot explain the reduced correlation of productivity with output seen in panel (a) of Figure 2.1.

The productivity correlations conditional on technology and demand shocks show that it is not the changing composition of various shocks hitting the economy that led to the productivity puzzle; rather, underlying structural changes like reduced labour market frictions have changed how the economy responds to the same shocks. Any successful explanation of the productivity puzzle should also confront these changes in conditional productivity correlations, and the model in Section 3 will achieve that.

[6]In Appendix A.3, I discuss the rationale behind the choice of this SVAR specification, along with the time-varying impulse responses and robustness to using TFP instead of ALP as the productivity measure.

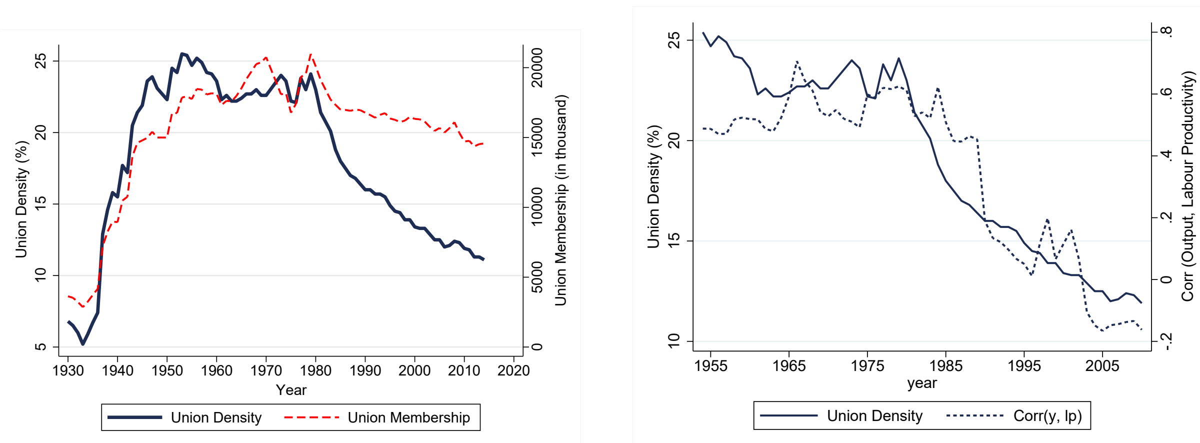
[7]A local projection analysis à la Jorda (2005) using utilization-adjusted TFP growth as the technology shock generates similar impulse responses for per capita hours worked (see Appendix A.3).

2.3 De-unionization: Why Did the Employment Adjustment Cost Drop?

So far, I have presented evidence for a decline in employment adjustment costs to explain the productivity puzzle. However, what observable structural change in the labour market can bring about such a sudden drop in hiring and firing costs remains an open question, which I address next.

2.3.1 The Productivity Puzzle and De-unionization: Timing and Speed

I consider various possible causes for a decline in the employment adjustment cost: the rise of online job search platforms, the increased use of temporary and part-time workers, and a decline in the job separation rate. I show in Appendix A.4 that none of these channels offers a satisfactory explanation for either the timing or suddenness of the productivity puzzle for the U.S. However, the decline of union power in the U.S. proves to be a better candidate for explaining the productivity puzzle.



(a) Union Membership Trend

(b) De-unionization & Productivity Puzzle

Figure 2.5: Timing and Speed of De-unionization & the Productivity Puzzle in the U.S.
Note: Panel (a) shows the number and percentage of non-agricultural wage and salary employees who are union members in the U.S. between 1930 and 2014. Union coverage rates differ slightly from union membership rates but follow a similar time trend. Data before 1977 is sourced from Historical Tables published by the BLS. 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 CPS, collected by Hirsch and Macpherson (2003). Panel (b) superimposes the union density in panel (a) with the rolling correlation of output and average labour productivity at business cycle frequencies in Figure 2.1a around the 1980s.

Panel (a) of Figure 2.5 shows that union membership among workers, both in terms of rates and absolute numbers, was rising in the U.S. until the early 1950s, after which it remained roughly flat for three decades, and started falling sharply from the early 1980s with a decline of roughly 50% by 2010. The decline in the private sector was more severe: a drop of 67% in the three decades post-1980.[8] The

[8] Aggregate union density was held roughly constant in the 1970s by falling rates in the private sector and a compensating rise in the public sector. Although de-unionization started in the early 1970s in the private sector, the process accelerated from 1980: the average annual rate of decline in private sector union density was 2.4% between 1974 and 1979 compared to 6.6% between 1980 and 1985 (see Hirsch and Macpherson (2003)). Based on a different data source extending before 1973, Troy and Sheflin (1985) find an average annual private-sector de-unionization rate of only 1.1% between 1950 and 1972. Therefore, it can be concluded that the decline of unions, even in the private sector, had a sharp acceleration from the early 1980s. In fact, the absolute number of union members peaked in 1979 before declining steadily.

decrease in size and influence of labour unions in the U.S. from the early 1980s lines up well in terms of both timing and speed with the productivity puzzle (see panel (b) of Figure 2.5).

Table 2.2: Long-Run Relationship between Union Density & Cyclicality of Labour Productivity in the U.S.

Period	Union Density	Corr.(ALP, Output)	Corr.(ALP, Employment)
Pre-1946	13.3%	0.42	-0.14
1947-1983	23.3%	0.77	0.20
Post-1984	14.2%	0.57	0.01

Note: Annual data between 1939 and 2019 on output and employment for the non-farm business sector in the U.S. is used. The output data is the real gross domestic value added from the BEA while the employment data is from the CES. ALP refers to average labour productivity defined as output per worker. The HP filter with a smoothing parameter of 6.25 is used to de-trend the variables. Union density figures are the averages in each of the three periods. See notes to Figure 2.5 for details about union density data.

The co-movement of union density and cyclicality of productivity around the 1980s is not an accident. Table 2.2 shows that before World War II, union density rose sharply and was accompanied by a rise in the procyclicality of productivity. In fact, the concept of labour hoarding was developed in the early 1960s as a response to the sudden increase in procyclicality of productivity immediately after the War. The overall long-run correlation between union density and the cyclicality of productivity with output from 1939 through 2019 is 0.60.

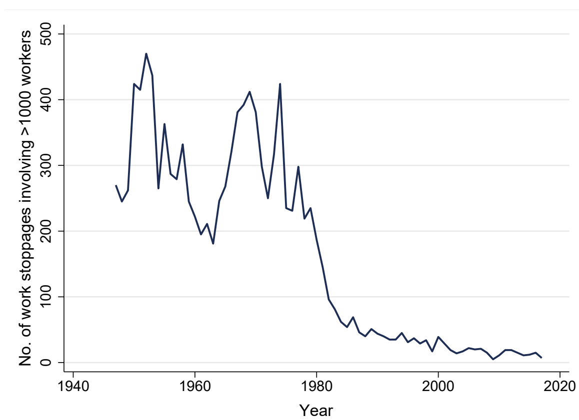


Figure 2.6: Number of Work Stoppages involving 1,000 or more workers in the U.S. (1947-2017)
Note: Data is sourced from the Economic News Release of the BLS.

Farber and Western (2002) show that the stark decline in union power was precipitated by an almost 50% fall between 1980 and 1985 in the annual number of union elections, a key channel for recruiting new union members. The unfavourable political climate for unions was strengthened by President Reagan's strong stand against the air-traffic controllers' strike of 1981,[9] and the much-

[9]On August 5, 1981, Reagan fired more than 11,000 striking air traffic controllers who had ignored his order to return to work. This sweeping mass firing of federal employees sent a strong message to American business leaders that they could hire and fire their workers much more easily.

publicized appointment of the Reagan Labor Board in 1983. The decline in union density may thus be an underestimate of the general loss in power of unions (see Taschereau-Dumouchel (2020)). One good proxy for the political clout of unions is the number of work stoppages organized by unions. Figure 2.6 shows that large-scale work stoppages dropped by almost 90% of their pre-1980 level quite suddenly within a couple of years. This sudden change in the influence of unions makes it a uniquely suitable candidate for explaining the strikingly rapid decline in cyclical productivity correlations.

2.3.2 The Productivity Puzzle and De-unionization: Evidence from U.S. Industries and States

One potential threat to the argument that de-unionization can explain the vanishing procyclicality of productivity in the U.S. is the possibility that most of the decline in union power could have happened simply through employment shifts towards less unionized industries and regions. In that case, if productivity were more countercyclical in sectors and regions with lower union density, then employment/output shifts towards such sectors would explain the vanishing procyclicality of aggregate productivity. However, decomposing the total change in union density, Δu into a within-change, $\sum_{i=1}^{I} \bar{e}_i \Delta u_i$ and a between-change, $\sum_{i=1}^{I} \bar{u}_i \Delta e_i$,[10] I find that de-unionization in the U.S. was primarily a within-industry and within-state phenomenon. About 88% and 92% of the fall in union density happened *within* industries and states, respectively, and not through employment shifts towards less unionized sectors and regions. This finding is encouraging for using cross-sectional variation in changes in union density across U.S. states and industries to see if a larger magnitude of de-unionization is correlated with a greater reduction in labour productivity correlation. In particular, I run the following regression:

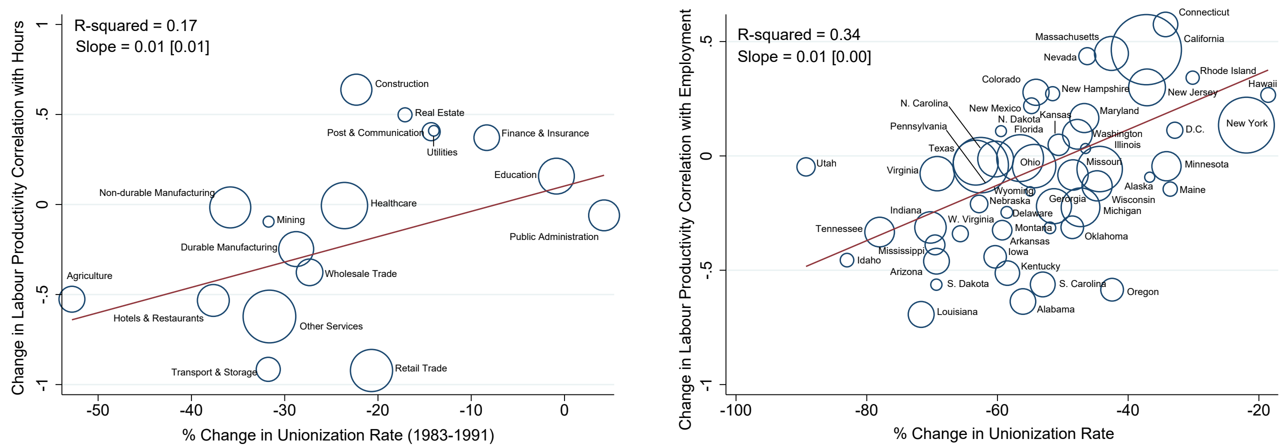
$$\Delta Corr\left(alp_i, labour_i\right) = \alpha + \beta \Delta \ln\left(\textit{Union Density}\right)_i + \varepsilon_i \tag{2.1}$$

where alp_i and $labour_i$ are the cyclical components of log average labour productivity and log total labour input in industry or state i. The Δ operator denotes the within-industry or within-state difference between the averages of the variables in the pre and post-1984 periods. For industries, I use real value added per hour as the measure of alp and total hours worked as the measure of $labour$. Since hours worked data is unavailable at the state level, I use non-farm state gross domestic product per worker and total employment as the corresponding measures. To avoid the results being driven by small industries or states, I weigh each observation by its average employment level over the entire period under study.

One important feature of this regression specification in time differences is that time-invariant characteristics of states and industries will not feature here and cannot lead to endogeneity. For instance, some industries might be more or less conducive to labour union activities for various reasons, e.g., mining workers might be more prone to form unions than their counterparts in financial

[10] Here, $\bar{e}_i$ is the average employment share and $\bar{u}_i$ is the average union density in industry or state i. I is 17 for industry-level decomposition and 51 for state-level decomposition.

services simply due to differences in the technology of production in the two sectors. However, so long such differential propensity of union activities across states and sectors is time-invariant, these fixed effects will be differenced out in specification (2.1).



(a) 17 U.S. Industries

(b) 51 U.S. States

Figure 2.7: Cross-Industry and Cross-State Evidence for De-unionization

Note: Data on industry and state-level union density comes from the CPS, collected by Hirsch and Macpherson (2003). Observations are weighted by the average employment in each industry or state, denoted by the bubble size. The p-values of the slope coefficients using robust standard errors are reported in parentheses. (a) Annual industry-level data on labour productivity (real value-added per hour), total hours and employment between 1947 and 2010 come from the KLEMS dataset, collected by Jorgenson, Ho and Samuels (2012). Industry codes in CPS and KLEMS were harmonized to create a consistent set of 17 U.S. industries. 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. The BK band-pass filter between 2 and 8 years has been used to de-trend the variables. (b) Annual state-level data on real non-farm gross domestic product per worker and total employment between 1969 and 2016 are sourced from the BEA. I use the annual growth rate to de-trend the variables because the preferred BK filter leaves only 3 years of data before 1984. All variable changes are calculated as the difference between the pre and post-1984 averages.

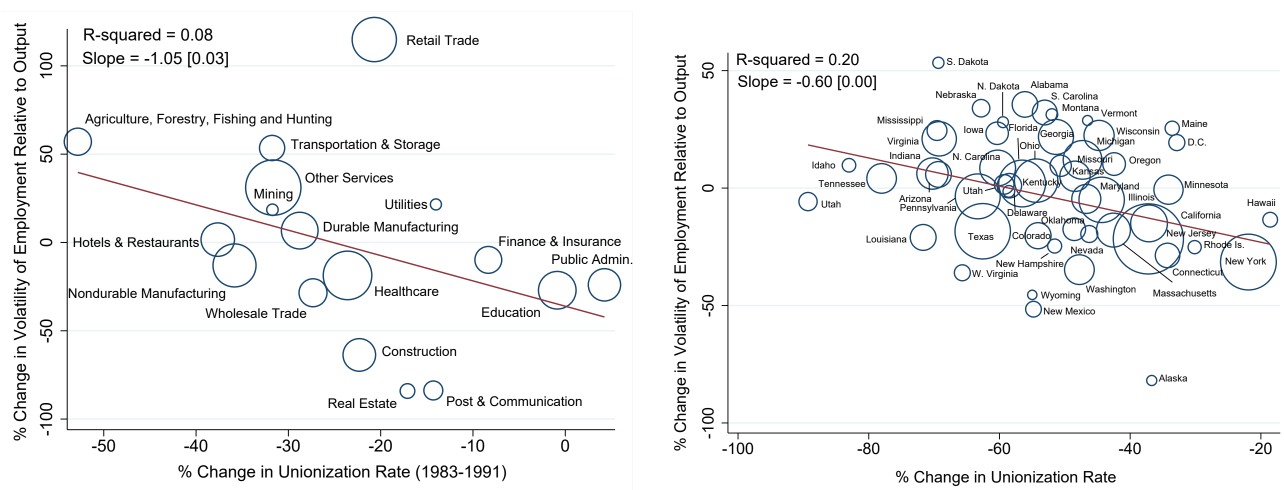
Figure 2.7 shows a significant positive relationship between the degree of de-unionization and the drop in productivity correlations across U.S. industries and states. Since de-unionization has been mostly within industries and states, for the cross-sectional results to be meaningful, it is important that the aggregate decline in procyclicality of productivity also happened due to reduced procyclicality within industries and states and not mostly due to reduced inter-sectoral and inter-state comovements. Using the same dataset, time horizon and cyclical filter as the industry analysis in panel (a) of Figure 2.7, I find that the mean-industry-employment weighted average of the within-industry changes in productivity correlations is -0.24 while the corresponding aggregate economy-wide change is -0.35. This implies that almost 70% of the decline in aggregate productivity procyclicality happened within the 17 industries considered here. Similarly, for panel (b) of Figure 2.7, I find that the mean-state-employment weighted average of the within-state changes in productivity correlations is -0.13 while the corresponding U.S.-wide change is -0.09, implying more than the entire change in the aggregate can be explained by within-state dynamics.[11]

[11]The implied aggregate economy-wide changes in productivity correlations are different in panels (a) and (b) of Figure 2.7, namely, -0.35 and -0.09, respectively. The difference arises because of different datasets (all-industry KLEMS data

For the state-level regression, there is an interesting heterogeneity in terms of right-to-work (RTW) legislation that potentially interacts with the role of unions. These RTW laws, known for their pro-business outlook, limit the role of labour unions in terms of employment protection. Therefore, one would not expect any significant change in productivity dynamics when union density declined in states with existing RTW laws. In Appendix Figures A.7 and A.8, I show this is indeed the case, with only the so-called non-RTW states driving the positive relationship between de-unionization and a drop in productivity correlation. This finding of RTW laws interacting with union power to determine productivity through changes in management practices resonates well with U.S. plant-level findings by Bloom et al. (2019).

An alternative identification strategy to the one 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 higher in sectors where a larger fraction of the workers is unionized to begin with. Thus, instead of regressing the change in the productivity correlation on the change in the union density, one 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 (see Appendix A.6).

2.3.3 De-unionization and the Reduction in Employment Adjustment Costs in the U.S.



(a) 17 U.S. Industries

(b) 51 U.S. States

Figure 2.8: Rising Relative Volatility of Employment and De-unionization across U.S. Industries & States
Note: See notes to Figure 2.7 for details regarding data sources and variable measurements.

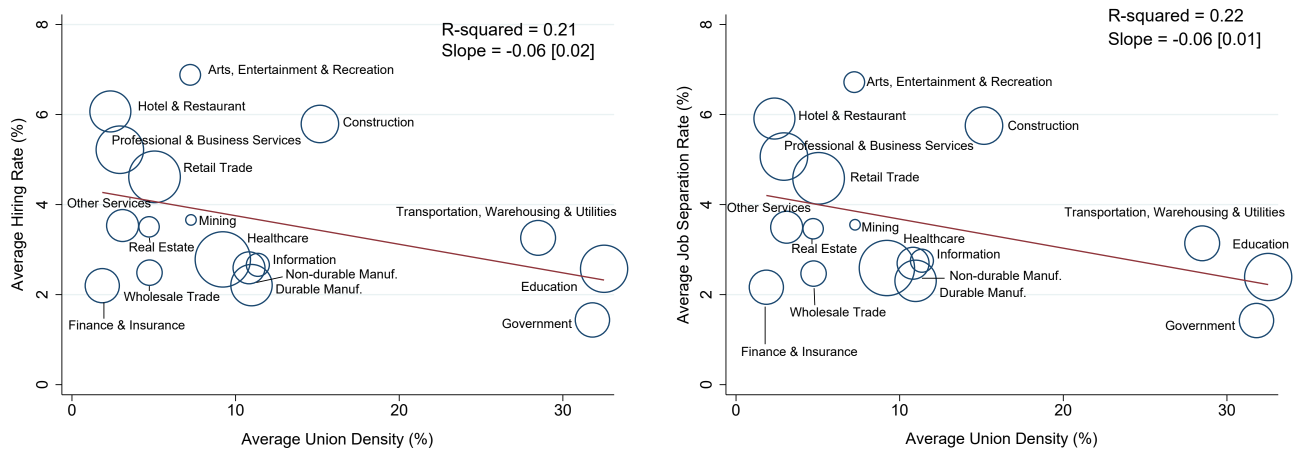
I have shown so far how de-unionization can explain the vanishing procyclicality of productivity in the U.S. economy. Nonetheless, the role of unions in explaining the productivity puzzle is specifically

versus non-farm GDP data from BEA), filters (BK-bandpass versus annual growth rate) and time horizons (1947-2010 versus 1969-2016). Nevertheless, to ensure parity, the within-industry and within-state changes have been compared to aggregate changes using the corresponding datasets, time horizons and filtering techniques.

through the channel of employment adjustment costs. More powerful unions can cause the employment adjustment costs to rise by forcing firms to hire from a restricted set of workers who are union members and/or demanding higher severance pay at the time of firing. For example, Del Boca and Rota (1998) find that for Italian manufacturing firms, employment adjustment costs increase by 40 times in cases of conflict with labour unions. Therefore, I now provide direct evidence that union density is indeed a significant determinant of hiring and firing costs.

In the absence of direct measures of labour market frictions, I focus on a proxy - the volatility of employment relative to the volatility of output. I find a statistically significant negative relationship between the change in the relative volatility of employment and the change in union density across U.S. industries and states (see Figure 2.8). This confirms the hypothesis that a decline in union power is correlated with a fall in employment adjustment cost.

Another proxy for employment adjustment cost is job flow rates. If unions hinder the hiring and firing of workers, one should expect industries with larger union presence to have lower job flow rates. I corroborate this conjecture by showing a statistically significant negative correlation between the average hiring and job separation rates on the one hand and the average union density on the other hand, across 17 U.S. industries (see Figure 2.9). This lends further credence to the link between unions and employment adjustment costs in the U.S.



(a) Hiring Rate

(b) Job Separation Rate

Figure 2.9: Job Flow Rates and Union Density across U.S. Industries

Note: Data on hiring and job separation rates for 17 U.S. industries come from the JOLTS dataset. Industry-wise union density and employment data are sourced from the CPS, collected by Hirsch and Macpherson (2003). Observation for each industry is weighted by its average employment level, denoted by the size of the bubble. The p-value of the slope coefficient using robust standard error is reported in parentheses. The analysis could not be carried out for the mid-1980s due to the lack of industry-level JOLTS data before 2001. To minimize the concordance error of industry codes between CPS and JOLTS, I use data between 2003 and 2017.

Apart from the cross-sectional evidence presented here, there are other studies which indicate a strong role of unions in increasing hiring and firing costs for firms in the U.S., e.g., Dunne, Klimek and Schmitz Jr. (2010) show that employment protection clauses put in the job agreements by labour unions during the 1960s and 1970s led to lower productivity in the U.S. cement industry, and when these employment protection clauses were removed in the 1980s due to much weaker union power, there were dramatic productivity improvements due to easier hiring and firing practices by firms across the industry. In addition, from a survey of 200 firms, Abraham and Medoff (1984) find that 92% of unionized firms have written rules about permanent layoffs while only 24% of non-union firms have any such policy, and this difference in employment protection policies translates to only 17% of union-sector employers firing workers based on productivity compared to 58% of non-union firms. Freeman and Medoff (1982) also highlight the substitution away from production workers towards other factors of production in the presence of higher labour costs in unionized manufacturing.

2.3.4 The Productivity Puzzle and De-unionization: International Evidence

The era of deregulation that began in the U.S. in the early 1980s had its parallel elsewhere. The U.K., which underwent similar changes under Margaret Thatcher, experienced both de-unionization and a drop in the procyclicality of productivity. On the other hand, countries like Canada, for which this decline in unionization is conspicuously absent (see Riddell (1993)), did not undergo a fall in cyclical productivity correlations. Figure 2.10 shows that in a sample of 13 OECD countries, de-unionization is strongly correlated with a loss in productivity procyclicality. This evidence is consistent in spirit with Gnocchi, Lagerborg and Pappa (2015), who identify union coverage as the labour market rigidity that most significantly impacts business cycle statistics in OECD countries.

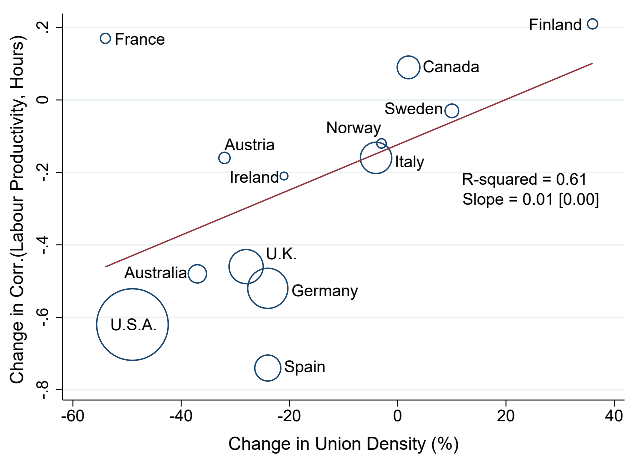


Figure 2.10: The Productivity Puzzle & De-unionization: International Evidence

Note: Union density data are sourced from *OECD Annual Trade Union Density Dataset*. Quarterly data on GDP, employment, total hours and labour productivity (real GDP per hour worked) 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*. HP filtered variables are used to calculate the change in productivity cyclicality. Changes in the variables refer to the change between the pre and post-1984 periods. Observations are weighted by the average employment level in each country, denoted by the size of the bubbles. The p-value of the slope coefficient using robust standard error is reported in parentheses.

One reason for de-unionization often proposed in the literature is skill-biased technological change (SBTC).[12] However, the fact that de-unionization did not occur in some advanced economies,

[12] Acemoglu, Aghion and Violante (2001) and Dinlersoz and Greenwood (2016) argue theoretically that SBTC can explain

like Canada, Sweden and Finland, makes it unlikely that the sudden trend reversal in union density in the U.S. was mainly driven by SBTC, which Berman, Bound and Machin (1998) have shown to have affected all developed economies. Furthermore, insofar as one believes that SBTC was driven by IT capital use (due to high capital-skill complementarity, highlighted by Krusell et al. (2000)), one should find a significant correlation across industries between the rising share of IT capital and falling productivity correlations. Wang (2014), however, points out that this is not the case. Thus, while it could be the case that technological changes impacting the labour market had some role to play in the long-term de-unionization process, the episode of rapid fall in union power from the early 1980s is most likely to have been caused by political factors that are exogenous to labour market conditions.

3 Model

In Section 2, I have argued that a drop in employment adjustment cost due to de-unionization caused the vanishing procyclicality of productivity during the mid-1980s in the U.S. I will now quantify the importance of this channel relative to other contemporaneous structural changes, namely, a higher nominal rigidity, a monetary policy more sensitive to inflation in the Volcker-era, and the reduced volatility of shocks during the Great Moderation.

To achieve this, I consider a New Keynesian model with two exogenous shocks — a technology shock to factor utilization-adjusted TFP and an aggregate demand shock. I choose this setup for a variety of reasons. First, the nominal rigidity in the New Keynesian framework generates the empirically observed negative response of labour input to a positive technology shock. Matching the empirical correlations of productivity with output and labour input conditional on technology and demand shocks is crucial to ascertain the changing role of different shocks in explaining the productivity puzzle. This is the main contribution of the current model compared to Galí and van Rens (2021), wherein an RBC-type model cannot match the conditional correlations of productivity. Second, having a monetary policy in the model allows me to quantify the role of a change in that policy in the 1980s in explaining the productivity puzzle. Third, the two-shock set-up directly mimics the SVAR analysis in the empirical section.

I consider both extensive and intensive margins of labour input adjustment (namely, employment and effort) and assume a time-varying convex cost of employment adjustment for firms. I do not model labour union behaviour explicitly because the key mechanism of improved labour market flexibility can be achieved by a host of factors like the rising use of temporary workers and online job search platforms, which are relevant for different countries at different periods (e.g., Jalón, Sosvilla-Rivero and Herce (2017) argue that the countercyclicality of labour productivity in Spain was driven by the 1984 legislative reform that made the hiring of temporary workers easier). Crucially, the absence of adjustment costs along the intensive margin in the model leads firms to depend more on

de-unionization, 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 the skill premium in wages. Foll and Hartmann (2019) argue that routine task-biased technical change is the driving force behind de-unionization.

effort adjustment when employment adjustment costs are high. This drives the main result of the vanishing procyclicality of labour productivity in the post-1984 era when hiring and firing frictions decreased significantly.

3.1 Households

Each household comprises a continuum of infinitely lived ex-ante identical members in 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. A fraction n_t of the household members are employed at time t, working h_t hours each and exerting effort e_t per hour. The household seeks to maximize the present value of expected lifetime utility, discounted at rate $\beta \in (0,1)$,

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\ln c_t - \tfrac{\mathcal{N}}{1+\eta} n_t^{1+\eta} - \tfrac{\mathcal{H}}{1+\gamma} n_t h_t^{1+\gamma} - \tfrac{\mathcal{E}}{1+\tau} n_t h_t e_t^{1+\tau} \right]$$

by choosing the path of per capita consumption c_t, bonds b_t and employment n_t, subject to the budget constraint,

$$c_t + b_t \leq w_t h_t n_t + D_t + T_t + b_{t-1} R_{t-1} / \pi_t.$$

Here, b_t denotes the holdings of one-period risk-free nominal bonds with a gross rate of return R_t, D_t are dividends from ownership of firms, w_t is the wage rate per hour, and π_t is the inflation rate between $t-1$ and t. Disutility from labour supply depends on the employment level, the number of hours per worker and the effort exerted per hour worked, with the corresponding non-negative weights in the per period utility function being $\mathcal{N}$, $\mathcal{H}$ and $\mathcal{E}$ respectively. There is a standalone disutility from employment, which is enhanced by the disutility from hours and effort only if the household member is employed and works positive hours. The non-negative elasticities η, γ and τ capture the curvature of labour disutility in employment, hours per worker and effort per hour, respectively. The household's equilibrium conditions are as follows:

$$\left[\mathcal{N} n_t^{\eta} + \frac{\mathcal{H}}{1+\gamma} h_t^{1+\gamma} + \frac{\mathcal{E}}{1+\tau} h_t e_t^{1+\tau} \right] c_t = w_t h_t \tag{3.1}$$

$$R_t E_t \left(\Lambda_{t,t+1} / \pi_{t+1} \right) = 1 \tag{3.2}$$

where $\Lambda_{t,t+k} \equiv \beta^k \frac{c_t}{c_{t+k}}$ $\forall t, k$ is the household's stochastic discount factor. Equation (3.1) is the intratemporal optimality condition, equating the marginal rate of substitution between employment and consumption to the wage per employed worker. Equation (3.2) is the standard intertemporal Euler equation. In addition to the above optimization problem, each worker also minimizes labour disutility by choosing a combination of hours and effort subject to a certain number of total effective hours, $e_t h_t n_t$ demanded by the firms. Details of this choice are presented in Section 3.3.

3.2 Firms

The production side of the economy has a final and an intermediate goods sector. Final goods producers are perfectly competitive. They aggregate the differentiated outputs from intermediate goods producers using the production function $y_t = \left(\int_0^1 y_{it}^{\frac{\varepsilon-1}{\varepsilon}} di\right)^{\frac{\varepsilon}{\varepsilon-1}}$, where y_{it} is the amount of good produced by the intermediate firm $i \in [0,1]$. The elasticity of substitution between the various intermediate goods is given by $\varepsilon > 1$. Minimization of the production cost, $\int_0^1 P_{it} y_{it} di$ by the final goods producers, subject to the production function above, yields the following demand function for the intermediate good i: $y_{it} = \left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} y_t$, where $P_t = \left(\int_0^1 P_{it}^{1-\varepsilon} di\right)^{\frac{1}{1-\varepsilon}}$ is the price of the final good, and P_{it} is the price of intermediate good i.

Households supply labour only to intermediate goods firms, who enjoy product market power, allowing them to charge a markup over marginal costs. Each intermediate goods firm, thus, chooses employment n_{it} and price P_{it} to maximize the expected stream of profits, discounted by the household's stochastic discount factor,

$$E_0 \sum_{t=0}^{\infty} \Lambda_{t,t+1} \left[(P_{it}/P_t)^{1-\varepsilon} y_t - w_{it} h_{it} n_{it} - \frac{\phi_p}{2} \left(\frac{P_{it}}{P_{i,t-1}} - 1\right)^2 y_t \right]$$

subject to the demand constraint,

$$(P_{it}/P_t)^{-\varepsilon} y_t = a_t \left(e_{it} h_{it} n_{it}\right)^{1-\alpha} - \frac{\phi_n}{2} \left(n_{i,t} - n_{i,t-1}\right)^2 \tag{3.3}$$

The right-hand side of the demand constraint is nothing but the intermediate goods production function net of any employment adjustment cost.[13] The variable a_t in the production function is the labour utilization-adjusted total productivity term, common to all firms. The log of a_t follows a first-order autoregressive process: $\ln a_t = \rho_a \ln a_{t-1} + \epsilon_t^a$, where $\epsilon_t^a \overset{\text{i.i.d.}}{\sim} N\left(0, \sigma_a^2\right)$. The parameter $\alpha \in (0,1)$ denotes the share of non-labour input in production. Since effort is unobserved in the data, the model counterpart of the empirically observed average labour productivity is $alp_t \equiv \frac{y_t}{n_t h_t}$.

The parameters $\phi_p \geq 0$ and $\phi_n \geq 0$ scale the Rotemberg (1982) price adjustment cost and the employment adjustment cost functions, respectively.[14] The choice to model labour market frictions as an employment adjustment cost function is best motivated in Heckman et al. (2000): *"...in the*

[13]One concern can be that whatever is being labelled as 'effort' in the production function is, in fact, capital, the missing factor of production. In Appendix B.2, 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. Empirically, it is hard to distinguish between capital utilization and labour utilization rates, e.g., Fernald (2014) uses hours per worker as the proxy for both labour and capital utilization, and the capacity utilization measure by the Federal Reserve is a combined measure of the intensive margin of all factors of production. Given this lack of identification of the intensive and extensive margins of labour and capital separately, I do not include capital in the analysis because it would be impossible to identify time variation in capital and employment adjustment costs separately. See Andrés, Boscá and Ferri (2013) for a model with capital market de-regulation explaining the productivity puzzle.

[14]The employment adjustment cost is assumed to be convex, following the finding in King and Thomas (2006). Cooper and Willis (2009) find non-convexity in aggregate labour adjustment cost using a model with fixed wages, but note that allowing for endogenous wage and price determination can make a convex adjustment cost more suitable for the aggregate economy even with non-convexity at the plant-level.

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..." However, since unions are thought to increase predominantly firing costs, in Section 4.3.2, I show the robustness of the model's quantitative results when a firing cost function is used instead of an employment adjustment cost that captures both hiring and firing frictions.

In a symmetric equilibrium, where $x_{it} = x_t$ for all i and t and for each variable $x \in \{w, e, h, n, P\}$,[15] the intermediate goods firm's first-order conditions with respect to employment and price are given as follows:

$$(1-\alpha)\frac{a_t\left(e_t h_t n_t\right)^{1-\alpha}}{n_t} - \phi_n\left(n_t - n_{t-1}\right) + \phi_n E_t\left[\Lambda_{t,t+1}\left(n_{t+1} - n_t\right)\right] = \frac{w_t h_t}{\Omega_t} \tag{3.4}$$

$$(1-\varepsilon) - \phi_p\left(\pi_t - 1\right)\pi_t + \phi_p E_t\left[\Lambda_{t,t+1}\left(\pi_{t+1} - 1\right)\pi_{t+1} y_{t+1}/y_t\right] = -\varepsilon\Omega_t \tag{3.5}$$

where Ω_t is the Lagrange multiplier associated with the firm's demand constraint (3.3) and reflects the real marginal cost of production. Equation (3.4) equates the marginal product of employment to the per worker wage rate, $w_t h_t$, divided by the real marginal cost Ω_t. Equation (3.5) is the standard New Keynesian Phillips curve.

The households own the firms, and all firm profits are paid out as dividends to the households. Therefore, we can write dividends as output net of wage payments and price adjustment costs:

$$D_t = y_t - w_t h_t n_t - \frac{\phi_p}{2}\left(\pi_t - 1\right)^2 y_t \tag{3.6}$$

3.3 Effort Per Hour and Hours Per Worker

In each period t, a worker in intermediate goods firm i chooses e_{it} and h_{it} to minimize the disutility from labour supply, $\ell_{it} \equiv \frac{\mathcal{N}}{1+\eta} n_{it}^{1+\eta} + \frac{\mathcal{H}}{1+\gamma} n_{it} h_{it}^{1+\gamma} + \frac{\mathcal{E}}{1+\tau} n_{it} h_{it} e_{it}^{1+\tau}$ subject to the firm's demand constraint (3.3). In a symmetric equilibrium, combining the first-order conditions for hours per worker and effort per hour yields the following equilibrium relation between effort and hours per worker:

$$e_t = \left(\frac{1+\tau}{\tau} . \frac{\mathcal{H}}{\mathcal{E}}\right)^{\frac{1}{1+\tau}} h_t^{\frac{\gamma}{1+\tau}} \tag{3.7}$$

Substituting equation (3.7) into the intermediate goods production function and the labour supply

[15] The presence of labour market frictions in the form of employment adjustment cost implies that wages, employment, effort and hours may differ across firms since they cannot be instantaneously arbitraged out by the free movement of workers from low to high wage firms. However, for simplification, I assume that new hires are paid the average wage prevailing at the firm and the number of workers is large enough for either the firm or the individual worker to internalize the effect of their choices on the average wage. This assumption is consistent with findings in Gertler and Trigari (2009), although Haefke, Sonntag and van Rens (2013) find greater wage flexibility for new hires. This assumption ensures that in a symmetric equilibrium, all workers receive the same wage equal to the ex-post average wage.

disutility function yields, respectively,

$$y_t = \left(\frac{1+\tau}{\tau}.\frac{\mathcal{H}}{\mathcal{E}}\right)^{\frac{1-\alpha}{1+\tau}} a_t \left(h_t^{1+\frac{\gamma}{1+\tau}} n_t\right)^{1-\alpha} - \frac{\phi_n}{2}\left(n_t - n_{t-1}\right)^2 \tag{3.8}$$

$$\ell_t = \frac{\mathcal{N}}{1+\eta} n_t^{1+\eta} + \frac{1+\gamma+\tau}{\tau\left(1+\gamma\right)} \mathcal{H} n_t h_t^{1+\gamma} \tag{3.9}$$

The equilibrium level of hours per worker is determined jointly by the firm and the worker to maximize the joint surplus from the employment relationship: $S_t \equiv \left[1 - \frac{\phi_p}{2}\left(\pi_t - 1\right)^2\right] y_t - c_t \ell_t$, which is the sum of the firm's profits D_t given by equation (3.6), and the household's wage earnings net of the consumption equivalent of labour supply disutility, $w_t h_t n_t - c_t \ell_t$. Using equations (3.8) and (3.9), and ignoring the terms in S_t not involving h_t, the optimization problem becomes

$$\max_{h_t} \left[1 - \frac{\phi_p}{2}\left(\pi_t - 1\right)^2\right] \left(\frac{1+\tau}{\tau}.\frac{\mathcal{H}}{\mathcal{E}}\right)^{\frac{1-\alpha}{1+\tau}} a_t \left(h_t^{1+\frac{\gamma}{1+\tau}} n_t\right)^{1-\alpha} - \frac{1+\gamma+\tau}{\tau\left(1+\gamma\right)} \mathcal{H} n_t h_t^{1+\gamma} c_t$$

The first order condition for hours per worker is given as follows:

$$(1-\alpha)\left(1 + \frac{\gamma}{1+\tau}\right)\left[1 - \frac{\phi_p}{2}\left(\pi_t - 1\right)^2\right] \frac{y_t + \frac{\phi_n}{2}\left(n_t - n_{t-1}\right)^2}{h_t} = \left(\frac{1+\gamma+\tau}{\tau}\right) \mathcal{H} n_t h_t^{\gamma} c_t \tag{3.10}$$

3.4 Closing the model

I assume a standard Taylor-type interest rate rule for the central bank,

$$R_t/\bar{R} = \left(\pi_t/\bar{\pi}\right)^{\psi_\pi} \tag{3.11}$$

where the parameter ψ_π measures the degree of responsiveness of the central bank to inflation. Since the Volcker era at the Federal Reserve, a more hawkish monetary policy implied a rise in ψ_π.

Bonds are assumed to be in net zero supply in equilibrium, implying $b_t = 0$. The government is assumed to balance its budget in every period but with an exogenous aggregate demand shock ν_t, which follows a first-order autoregressive process in logs: $\ln \nu_t = (1-\rho_\nu)\ln \bar{\nu} + \rho_\nu \ln \nu_{t-1} + \epsilon_t^\nu$, where $\epsilon_t^\nu \overset{\text{i.i.d.}}{\sim} N\left(0, \sigma_\nu^2\right)$. I take the steady-state value of the aggregate demand shock, $\bar{\nu} = 0.20$, reflecting the average share of government expenditure in GDP. Using the equilibrium conditions for bonds and the government budget, we can re-write the households' budget constraint as the aggregate goods market clearing condition:

$$c_t + \nu_t = \left[1 - \frac{\phi_p}{2}\left(\pi_t - 1\right)^2\right] y_t \tag{3.12}$$

Competitive Equilibrium is a set of sequences $\{\pi_t, w_t, R_t, \Omega_t, n_t, e_t, h_t, c_t, y_t\}_{t=0}^{\infty}$ that satisfy the household's optimality conditions (3.1) and (3.2), the production function (3.8), the firm's demand for employment (3.4), the price-setting condition (3.5), the optimality conditions for effort (3.7) and hours (3.10), the interest rate rule (3.11), and the aggregate accounting condition (3.12), conditional on the exogenous processes for the technology and demand shocks, $\{a_t, \nu_t\}_{t=0}^{\infty}$. I collect the complete set of equilibrium conditions in Appendix B.1.

4 Quantitative Analysis

I calibrate the model parameters and then check how far structural changes in some of them between the pre and post-1984 periods can explain the productivity puzzle.

4.1 Calibration

For ease of exposition, I discuss the calibration of the entire set of parameters in five groups: (i) the parameter affected by de-unionization, namely, the decline in the employment adjustment cost parameter, ϕ_n; (ii) the parameter dictating the level of nominal rigidity, ϕ_p, which increased in the post-1984 period; (iii) the monetary policy parameter, ψ_π, which increased in the Volcker era; (iv) the volatilities of the exogenous shocks to technology and aggregate demand, σ_a and σ_ν, which decreased in the period of Great Moderation; and (v) all other parameters that I will consider to have remained stationary over the period under study. The complete list of these parameters and their calibrated values are presented in Table 4.1.

Stationary parameters. I assume most of the parameters to have remained constant between the pre and post-1984 periods. These are calibrated to well-established estimates in the literature.

The discount factor β is set to 0.99 for quarterly data, implying a real risk-free annual interest rate of approximately 3%. Following Dossche, Gazzani and Lewis (2023), I calibrate the parameter ε to 7.50, which translates to a price markup of 15% over marginal cost. The share of non-labour inputs in the total factor cost of production, α is set at 0.33. Following Cho and Cooley (1994), the elasticity of labour supply disutility with respect to employment is set at 2, implying a value of 0.50 for η. The elasticity of disutility to hours per worker is estimated to be 0.50 in Chetty et al. (2012), which implies a value of 2 for γ. The joint values of α, γ and τ have implications for the return to scale of hours per worker in the production function. As seen from the production function (3.8), $(1-\alpha)\left(1+\frac{\gamma}{1+\tau}\right)$ is the return to hours per worker, which has been estimated to be between 1.28 and 1.60 in Basu, Fernald and Kimball (2006), implying a short-run increasing return to hours per worker. Barnichon (2010) assumes a value of 1.50 in that range, which I use in the baseline calibration to pin down τ at 0.60. Finally, the persistence of the technology and demand shocks are taken from estimates in Dossche, Gazzani and Lewis (2023).

Taylor rule response to inflation. Clarida, Galí and Gertler (2000) find an increase in the Taylor rule parameter, ψ_π from 0.86 to 2.55, between the pre-Volcker era and the post-1982 period. I do not allow ψ_π to be lower than 1 to avoid indeterminacy of multiple equilibria. Instead, I take the pre and post-1984 values of 1.01 and 2.20 for ψ_π respectively, which are the values used by Clarida, Galí and Gertler (2000) themselves in their simulations.

Table 4.1: Baseline Calibration of Parameters

Parameter	**Value**	**Calibration - Target & Source**
β	0.99	Real risk-free annual interest rate $\simeq 3\%$
ε	7.50	Mark-up over marginal cost $\simeq 15\%$; Dossche, Gazzani and Lewis (2023)
α	0.33	Share of non-labour input in total compensation
η	0.50	Elasticity of disutility to employment $\simeq 2$; Cho and Cooley (1994)
γ	2.00	Elasticity of disutility to hours per worker $\simeq 0.5$; Barnichon (2010), Chetty et al. (2012)
τ	0.60	$(1-\alpha)\left(1+\frac{\gamma}{1+\tau}\right) \simeq 1.50$; Barnichon (2010)
ψ_π	(1.01, 2.20)	Taylor rule response to inflation pre and post-1984; Clarida, Galí and Gertler (2000)
ϕ_p	(8.44, 11.21)	Phillips curve coefficient, $\frac{\varepsilon-1}{\phi_p} \simeq 0.77$ and 0.58 pre and post-1984; Lubik and Schorfheide (2004)
ϕ_n	(2.56, 1.21)	$s.d.(n)/s.d.(y) = 0.70$ and 0.97 pre and post-1984; Simulated Method of Moments
ρ_a	0.215	Persistence of technology shock; Dossche, Gazzani and Lewis (2023)
ρ_ν	0.774	Persistence of demand shock; Dossche, Gazzani and Lewis (2023)
σ_a	(0.007, 0.006)	Standard deviation of technology shock pre and post-1984; Dossche, Gazzani and Lewis (2023)
σ_ν	(0.128, 0.083)	Standard deviation of demand shock pre and post-1984; Dossche, Gazzani and Lewis (2023)

Note: Parameters with a pair of values (v_1, v_2) are allowed to change from v_1 to v_2 between the pre and post-1984 calibrations in our baseline simulation in Table 4.2.

Nominal rigidity. Smets and Wouters (2007) find a significant rise in nominal rigidity in the post-1984 period because of the reluctance of firms to change prices in an era of low inflation. In my model, an increase in nominal rigidity would show up as an increase in the Rotemberg (1982) scale parameter, ϕ_p. Lubik and Schorfheide (2004) find that the Phillips curve coefficient $\frac{\varepsilon-1}{\phi_p}$ has decreased from 0.77 in the pre-1984 period to 0.58 in the post-1984 era. Since I have calibrated ε to 7.50, the pre and post-1984 values of ϕ_p are pinned down at 8.44 and 11.21, respectively, implying a rise in nominal rigidities.

Volatilities of technology and demand shocks. The reduction in shock volatilities captures the Great Moderation in the U.S. economy since the early 1980s. I use the volatility estimates in Dossche, Gazzani and Lewis (2023) for the post-1984 period. The pre-1984 values are calculated to reflect a reduction of 5.6% and 25.5% in the standard deviations of the technology and demand shocks, respectively in the post-1984 era. The magnitudes of the changes reflect changes in the cyclical volatilities of log utilization-adjusted TFP and log share of government expenditure in GDP, respectively. This ensures that, consistent with findings in Barnichon (2010), the reduction in the technology shock volatility is lower than that in the demand shock volatility, such that technology shocks have become relatively more important in the post-1984 era.

Employment adjustment cost. Having calibrated all the parameters except ϕ_n, I estimate it through a simulated method of moments by equating the model simulated value to the empirical value of the standard deviation of employment relative to that of output separately for the pre and post-1984 periods. The estimation yields values of 2.56 and 1.21 for ϕ_n before and after 1984, respectively. The post-1984 reduction in ϕ_n reflects a lower employment adjustment cost.

4.2 Quantitative Performance of the Model

Table 4.2 studies the effect of the various parameter changes noted in Table 4.1, one at a time. Here, I focus on the changes in the moments between the pre and post-1984 periods, while the levels of the moments in the two sub-periods are noted in Appendix Table C.1.

Table 4.2: Changes in Business Cycle Moments between Pre and Post-1984

Business Cycle Moments		**Changes in Moments between Pre & Post-1984 due to Parameter Changes**			
		Model			
	Data	**Union:** ϕ_n	**Nominal Rigidity:** ϕ_p	**Monetary Policy:** ψ_π	**Shock Volatility:** σ_a,σ_ν
	(1)	(2)	(3)	(4)	(5)
I. Labour Productivity Correlations					
A. Unconditional Moments					
Output: $Corr\left(y_t, alp_t\right)$	-0.61	-0.38	-0.13	+0.35	+0.04
Hours: $Corr\left(n_t h_t, alp_t\right)$	-0.65	-0.36	-0.14	+0.44	-0.02
Employment: $Corr\left(n_t, alp_t\right)$	-0.60	-0.22	-0.11	+0.37	+0.00
Hours Per Worker: $Corr\left(h_t, alp_t\right)$	-0.60	-0.15	-0.02	+0.13	-0.04
Effort: $Corr\left(e_t, alp_t\right)$	-0.53	-0.15	-0.02	+0.13	-0.04
B. Conditional on Technology Shock					
Output: $Corr\left(y_t, alp_t\right)$	+0.19	-0.02	-0.02	+0.03	-
Hours: $Corr\left(n_t h_t, alp_t\right)$	-0.06	-0.06	-0.01	-0.00	-
C. Conditional on Demand Shock					
Output: $Corr\left(y_t, alp_t\right)$	-1.21	-0.58	-0.19	+0.54	-
Hours: $Corr\left(n_t h_t, alp_t\right)$	-1.24	-0.52	-0.20	+0.66	-
II. Absolute & Relative Volatilities					
Output: $s.d.\left(y_t\right)$	-36%	+5%	+1%	-3%	-24%
Employment: $s.d.\left(n_t\right)$	-12%	+45%	+17%	-43%	-24%
Employment to Output: $s.d.\left(n_t\right)/s.d.\left(y_t\right)$	+39%	+39%*	+16%	-41%	0%

Note: All columns report changes in moments of BK bandpass filtered (between 6 and 32 quarters) log variables between pre and post-1984 periods (1956-1983 and 1984-2011). ALP is defined as output per hour worked. Factor utilization rate from Ramey (2016) based on Fernald (2014) is used to measure effort in data. The data moments reported for productivity correlations conditional on technology and demand shocks are taken from Table 5 of Galí and Gambetti (2009). Column (1) reports the empirically observed changes in the business cycle moments. Columns (2) through (5) show the moment changes due to specific parameter changes in the model simulations. Column (2) reduces ϕ_n from 2.56 to 1.21 to match the rise in the volatility of employment relative to that of output (the * marked value of +39%); column (3) changes the Rotemberg price adjustment cost parameter ϕ_p from 8.44 to 11.21 to reflect a higher level of nominal rigidity; column (4) changes the Taylor rule parameter ψ_π from 1.01 to 2.20; and column (5) reduces the shock volatilities σ_a and σ_ν by 5.6% and 25.5% respectively.

De-unionization. Column (1) of Table 4.2 reports the empirically observed changes in business cycle moments between the pre and post-1984 periods. Column (2) reports the changes in moments due to the decline in the employment adjustment cost parameter ϕ_n to match the 39% increase in the relative volatility of employment. Figure 2.8b found that a 1% decline in union density was associated with a 0.6% increase in the relative volatility of employment. Therefore, a 39% increase in the relative volatility of employment should be associated with a 65% decline in union density. In fact, between the pre and post-1984 periods, private sector union density in the U.S. declined by roughly that amount (63% to be precise). Thus, the moment changes in column (2) of Table 4.2 can be interpreted as the total effect of the U.S. de-unionization episode of the early 1980s.[16]

Comparing columns (1) and (2) reveals that the drop in the employment adjustment cost due to de-unionization can explain about 63%, 55% and 37% of the empirically observed drops in the correlations of productivity with output, total hours worked and employment, respectively. The model also captures almost half of the decline in productivity procyclicality conditional on a demand shock. The finding that a fall in productivity correlations conditional on a demand shock drives the reduction in unconditional moments implies that demand shock must be the main source of variation for output and labour dynamics over the business cycle. Many authors have empirically corroborated this, starting from Burnside, Eichenbaum and Rebelo (1993). The changes in the absolute volatilities of output and employment implied by easier employment adjustment go in the opposite direction of the data. The model needs to have less volatile shocks to account for the empirical decline in absolute volatilities of these variables during the Great Moderation.

Figure 4.1: Role of Employment Adjustment Cost in Explaining the Productivity Puzzle
Note: The dashed lines plot 15-year centred rolling window correlations of BK bandpass filtered (between 6 and 32 quarters) average labour productivity (output per hour worked) with output (left panel) and employment (right panel) in the U.S. between 1954 and 2008. The solid lines plot the year-wise correlations of average labour productivity with output and employment as implied from model simulations by changing the employment adjustment cost parameter ϕ_n to match year-wise employment volatility relative to output. The means of the model-implied correlation series between 1954 and 2008 have been shifted by a constant to match their empirical counterparts, keeping the dynamics unchanged.

Going beyond the pre and post-1984 calibration, I test the model's performance for explaining the productivity puzzle through year-to-year changes. In Figure 4.1, I estimate the employment adjustment cost parameter, ϕ_n, to match the empirical and model-implied values of the relative volatility of employment for every year between 1954 and 2008. The resulting simulated correlations of labour productivity with output and employment follow their empirical counterparts closely, with correlation coefficients of 0.95 and 0.91 for the productivity correlations with output and employment, respectively. Thus, the channel of time-varying employment adjustment cost matches not only the change in productivity correlations between the pre and post-1984 periods but also the entire

[16]To have a conservative estimate of the quantitative role of the de-unionization channel, I have used the flatter slope between union density and relative volatility of employment across states (0.60 from Figure 2.8b) instead of the steeper one across industries (1.05 from Figure 2.8a). Using the steeper slope will increase the explanatory power of the de-unionization channel.

cyclical dynamics of productivity for more than half a century.

Reduced nominal rigidity. Column (3) of Table 4.2 shows that while the drop in nominal rigidity in the post-1984 era goes some way in explaining the productivity puzzle, the magnitude of the changes are quite small, particularly in comparison to the changes due to the decline in the employment adjustment cost.

Hawkish monetary policy. Column (4) of Table 4.2 shows that a monetary policy more sensitive to inflation in the post-1984 period made average labour productivity more procyclical and thus counteracted the productivity puzzle.

Asymmetric reduction in shock volatilities. Technology shock induces a negative correlation between employment and productivity in the data as well as in the model. Despite this, its enhanced importance relative to demand shock in the post-1984 period cannot explain the more countercyclical productivity in the post-1984 period (see column (5) of Table 4.2). While the reduction in shock volatilities during the Great Moderation cannot explain the vanishing procyclicality of productivity, it is key to match the drop in absolute volatilities of the macro-variables. The reconciliation between a decreased labour market turnover (see Decker et al. (2020)) and higher relative volatility of employment is made possible in the model through two channels: a drop in the cost of employment changes (this makes employment more volatile than output and effort) and a drop in the volatilities of shocks (this makes the absolute volatilities of all variables including employment to decline).

4.3 Robustness

4.3.1 Labour Supply Elasticities

Barnichon (2010) argues that longer working hours are more strenuous in the manufacturing sector than in the service sector. Hence, with the shift of the industry composition towards the service sector, one would expect a lower disutility cost of hours per worker, reflected in a lower γ in the post-1984 period. Barnichon (2010) estimates γ to be 3.20 in the pre-1984 period and 0.80 in the post-1984 era. Moreover, he estimates a decline in $(1-\alpha)\left(1+\frac{\gamma}{1+\tau}\right)$, the short-run increasing returns to hours per worker from 1.9 to 1.0 between the two periods, thereby implying a corresponding decrease in the elasticity of effort parameter, τ from 0.74 to 0.60. Allowing the employment adjustment cost parameter ϕ_n to be re-calibrated in the two sub-periods when the declines in γ and τ are taken into account betters the quantitative performance of the model relative to the baseline of no change in the labour supply elasticities (see Appendix Table C.2).

4.3.2 Firing Cost

I have modelled labour market frictions in the baseline framework as an employment adjustment cost. However, unions are typically thought of as increasing predominantly the firing cost. Therefore, I study the model's quantitative performance when I use a firing cost to model labour market frictions instead of the employment adjustment cost. The firing cost function is defined as $\phi_f.\max\left(n_{t-1}-n_t,0\right)$, where ϕ_f captures the size of the firing cost. Note that the function is not differentiable, but following the technique introduced in Llosa et al. (2014), it can be approximated by the differentiable function $\frac{\phi_f}{2}\left[(n_{t-1}-n_t)+\sqrt{(n_{t-1}-n_t)^2+\kappa}\right]$, where $\kappa > 0$ is the approximation parameter, set to 0.001. Appendix Table C.3 shows that the quantitative performance of the model under this firing cost specification is similar to the baseline with employment adjustment cost.

5 Other Plausible Explanations

Having shown that lower employment adjustment costs due to de-unionization can quantitatively account for the productivity puzzle, I now argue that some other potential explanations either do not hold up to empirical scrutiny or are inconsistent with some features of the U.S. business cycle.

5.1 Vanishing Countercyclicality of Labour Quality

If firms fire their least productive workers in recessions, the average productivity of the workers remaining in the workforce rises in economic downturns, making productivity more countercyclical. Now, if firms are doing this selective firing more intensely after the mid-1980s due to either a greater ability to measure individual worker productivity (possibly due to the availability of better monitoring technology) or greater ease of hiring and firing workers (possibly due to factors like de-unionization), then it could explain the productivity puzzle (see Berger (2016)).

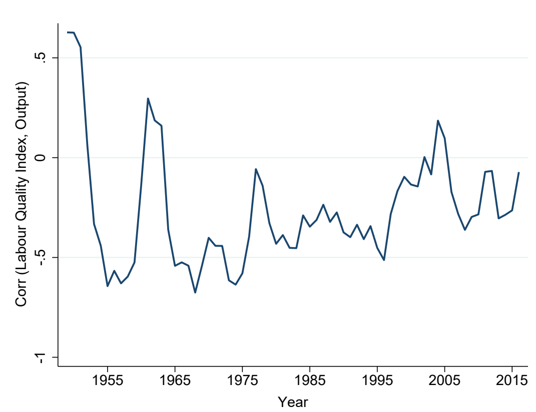


Figure 5.1: Cyclical Correlation of Labour Quality Index with Output

Note: Labour Quality Index and output data for U.S. business sector is sourced from Fernald (2014). The measure of labour quality used is the Labour Quality Index constructed by Aaronson and Sullivan (2001) from 1979 onwards using CPS data on individual worker's wage, sex, job experience and education, while the pre-1979 data is the annual BLS Multi-Factor Productivity estimate of labour composition interpolated by Fernald (2014) using the method outlined in Denton (1971).

To ascertain if this is indeed the case, I compute the rolling window correlation of a measure of labour quality with output along the business cycle in Figure 5.1. I find that while it is true that labour quality rises in recessions (as evident from the negative cyclical correlation of labour quality with output), there is no evidence that this phenomenon has intensified in the post-1980 period (there is no discernible difference in the correlation before and after the 1980s). Notwithstanding the possibility that firms have more information on individual worker productivity than is captured through the Labour Quality Index, this finding implies that the greater ease of hiring and firing workers did not translate into a more selective firing of low-quality workers during recessions but rather more employment adjustment for all workers or the 'average-quality representative' worker.

5.2 Rise of the Service Sector: Composition and Substitution Effects

Table 5.1: Cyclicality of Labour Productivity in Manufacturing & Services

	Corr.(ALP, Output)			**Corr.(ALP, Hours)**		
Sector	Pre-1983	Post-1984	Change	Pre-1983	Post-1984	Change
Manufacturing	0.63	0.40	-0.23	-0.04	-0.30	-0.26
Services	0.68	0.48	-0.20	-0.10	-0.59	-0.49

Note: Data is sourced from the annual KLEMS dataset between 1947 and 2010 by aggregating industry-level non-additive chained indices using the cyclical expansion method in Cassing (1996). Results are robust to using the annual sectoral dataset from BEA, compiled by Herrendorf, Herrington and Valentinyi (2015).

The rise of the service sector can have a *composition effect* on the cyclical productivity correlations. If the service sector has more countercyclical labour productivity (arguably due to more flexible working hours than in manufacturing), then a simple compositional shift in the share of value-added and employment towards services can explain the decline in the aggregate productivity correlations. However, the labour productivity correlations in Table 5.1 show that manufacturing and service sectors had similar productivity correlations before the mid-1980s and experienced a similar drop in those correlations. Moreover, the compositional shift towards services has been too gradual to explain the sudden drop in productivity correlations.

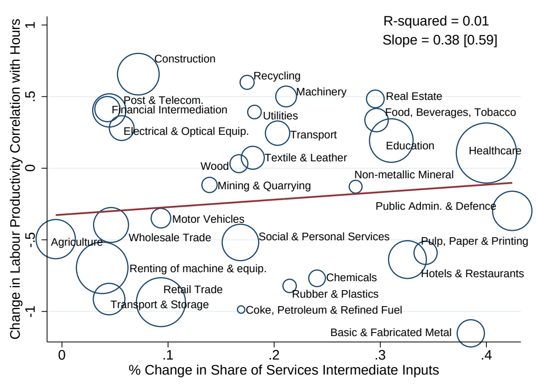


Figure 5.2: Services Intermediate Input Share & Cyclicality of Labour Productivity

Note: Data is sourced from the annual KLEMS dataset between 1969 and 2010. Time changes refer to the difference between the average values in the pre and post-1984 periods. Regression is weighted by the time average of total hours worked in each industry, 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. The result is robust to using other filters.

The rise of services can also contribute towards falling aggregate productivity correlations through the *substitution effect*: if there is a larger share of services intermediate inputs in the economy, then all sectors' labour productivity will mimic that of the services sector.[17] While all non-farm industries witnessed a sharp rise in the share of services intermediate inputs from the early 1980s, I do not find any negative relationship between the rise in the share of services intermediate input usage and the decline in the labour productivity correlations across 31 U.S. industries (see Figure 5.2).

5.3 Growing Share of Intangible Capital

One explanation for the productivity puzzle is the mismeasurement of output: if a part of the output is not measured and if this omitted portion is more positively correlated with labour input than the measured part, then the measured labour productivity correlation can be lower than the true one. McGrattan and Prescott (2012) argue that intangible capital is one such source of mismeasurement, 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, McGrattan and Prescott (2012) analyze the U.S. business cycle only between 2004 and 2011. Nevertheless, it is important to corroborate whether their explanation is supported by data when the correct time period is considered.

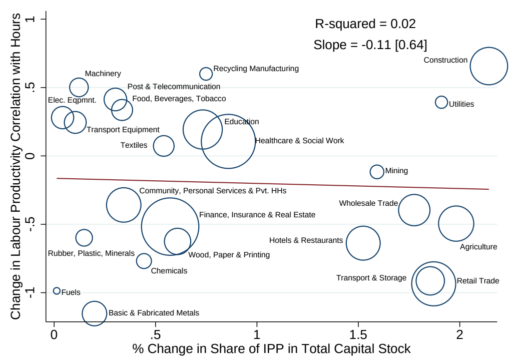


Figure 5.3: Share of Intellectual Property Product Capital & Cyclicality of Labour Productivity

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 band-pass filter between 2 and 8 years has been used to extract the cyclical component of the variables. The result is robust to using other filters.

McGrattan and Prescott (2012) define 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."* The closest measure to this definition in aggregate U.S. data is investment in intellectual property products (IPP). IPP contains research and development, computer software

[17]This idea of an evolving input-output structure leading to a switch in the cyclicality of productivity can be found in Huang, Liu and Phaneuf (2004) and vom Lehn and Winberry (2022).

and databases, and artistic originals (see Appendix D.1 for details). While IPP investment picked up from the late 1970s in most 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).

5.4 Aggregate versus Sectoral Shocks

Reallocation of factors of production towards firms and industries with higher marginal products of inputs can boost aggregate productivity. Thus, if productivity-enhancing inter-sectoral reallocation of resources has become more prevalent during recessions since the mid-1980s, then it could explain the vanishing procyclicality of measured productivity. Foster, Grim and Haltiwanger (2016) find that downturns are indeed periods of accelerated factor reallocation that is productivity-enhancing. Still, the intensity of reallocation fell rather than rose for the Great Recession of 2007-08, and the reallocation that did occur was less productivity-enhancing than in prior recessions. This reflects earlier findings in Aaronson, Rissman and Sullivan (2004), who show that reallocation of employment across industries has declined over the recent business cycles. Moreover, since most U.S. industries have individually experienced a decline in procyclicality of productivity, it seems unlikely that inter-industry factor reallocation is the main explanation for the productivity puzzle.

Garin, Pries and Sims (2018) and vom Lehn and Winberry (2022), however, argue that sector-specific shocks have become more important relative to economy-wide shocks in the post-1984 period (see Foerster, Sarte and Watson (2011)), and this phenomenon can explain the drop in productivity correlations. To explain the productivity puzzle Garin, Pries and Sims (2018) rely on sector-specific shocks generating counterfactual negative co-movement of employment across sectors, while vom Lehn and Winberry (2022) rely on sectoral shocks to 'investment hubs' with countercyclical productivity accounting for an increasing share of aggregate fluctuations since the 1980s. Using industry-level data from various sources — BEA, CES, KLEMS and Index of Industrial Production (IIP), I show that the main finding of sectoral shocks becoming more important than economy-wide shocks is not robust. For example, when the 31-industry classification from KLEMS data or the 20-industry classification from IIP data is considered, sector-specific shocks appear to have become less important in the post-1984 era (see Appendix D.2 for details). However, a shift towards sectoral shocks to investment hubs with countercyclical productivity, highlighted by vom Lehn and Winberry (2022) remains a valid possibility, albeit with the caveat that their mechanism cannot reconcile with the empirically observed changes in the productivity correlations conditional on technology and demand shocks.

6 Conclusion

Barnichon (2010) writes "*...the weaker procyclicality of productivity after 1984 is the result of a more flexible labor market with lower hiring frictions...Exploring what factors (...) could have increased the flexibility of the labor market is thus an important task for future research.*" This paper has been an attempt in that research direction. It shows that a lower dependence on labour hoarding by firms, faced with reduced costs of hiring and firing workers due to a rapid decline in labour union power, caused the vanishing procyclicality of productivity in the U.S. Cross-sectional evidence from U.S. states and industries show that de-unionization can predict both the loss in procyclicality of productivity and the rising ease of employment adjustment. A New Keynesian model with endogenous effort choice and a time-varying employment adjustment cost can generate empirically observed changes in the key business cycle moments. The model also brings forth the limited influence of other contemporaneous structural changes, like the Great Moderation and a more accommodative monetary policy, as potential explanations for the productivity puzzle. The increased selective firing of less productive workers during recessions, the sectoral shift from manufacturing to services, the increased use of intangible capital, the advent of online recruitment, the higher share of "just in time" hiring, and the increased productivity-enhancing inter-sectoral factor reallocation during recessions, have little empirical validity as explanations for the productivity puzzle.

A world with less procyclical productivity and higher relative volatility of employment brings instability to workers' jobs. Policy prescriptions, like short-term work policies that encourage labour hoarding by firms during recessions, can be envisaged to reduce job loss risks. Giupponi and Landais (2023) show that such policies in Italy stabilized employment and brought small positive welfare gains during the Great Recession. Graves (2023) shows that in the U.S. firing taxes are more effective than hiring subsidies in stabilizing employment along the business cycle. Further research can shed light on these welfare implications of policy-making in a world with countercyclical productivity.

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Appendix

A Appendix to Section 2

A.1 Robustness of Business Cycle Moments to Choice of Filters and Datasets

In this appendix, I present the cyclical correlations and volatilities of different variables using various 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) KLEMS dataset (compiled by Jorgenson, Ho and Samuels (2012)) that contains annual data on ouput, hours, employment, labour productivity and growth rate of TFP for the aggregate U.S. economy; (ii) Fernald (2014) 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 (iv) the quarterly capacity utilization rate from the Federal Reserve Board (FRB) based on the Quarterly Survey of Plant Capacity (QSPC) by the Census Bureau.

Apart from quarterly and annual growth rates, I have considered two other time-series filters: (i) Hodrick and Prescott (1997) (HP) 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 for quarterly data or between 2 and 8 years for annual data. 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 Noullez (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.1: Cyclical Correlations of Output per Hour

	With Output			**With Hours**			**With Employment**		
Dataset & Filter	Pre 1983	Post 1984	Change	Pre 1983	Post 1984	Change	Pre 1983	Post 1984	Change
Panel A: LPC Data									
Hodrick-Prescott	0.61	-0.01	-0.62	0.15	-0.53	-0.68	0.05	-0.59	-0.64
BK-Bandpass	0.56	-0.03	-0.59	0.12	-0.53	-0.65	0.01	-0.58	-0.59
Quarterly Growth Rate	0.71	0.53	-0.18	0.02	-0.34	-0.36	-0.02	-0.33	-0.31
4-Quarter Growth Rate	0.63	0.23	-0.40	0.08	-0.37	-0.45	-0.04	-0.37	-0.34
Annual Growth Rate	0.64	0.16	-0.48	0.12	-0.40	-0.52	-0.03	-0.40	-0.37
Panel B: KLEMS Data									
Hodrick-Prescott	0.35	-0.02	-0.37	-0.22	-0.62	-0.40	-0.28	-0.60	-0.32
BK-Bandpass	0.42	0.32	-0.10	-0.16	-0.51	-0.35	-0.33	-0.42	-0.10
Annual Growth Rate	0.53	0.22	-0.31	-0.10	-0.32	-0.22	-0.14	-0.24	-0.10

Table A.2: Cyclical Volatility of Output, Hours & Employment

Dataset & Filter	s.d.(Output) Pre-1983	s.d.(Output) Post-1984	s.d.(Output) $\frac{Post}{Pre}$	s.d.(Hours) Pre-1983	s.d.(Hours) Post-1984	s.d.(Hours) $\frac{Post}{Pre}$	s.d.(Employment) Pre-1983	s.d.(Employment) Post-1984	s.d.(Employment) $\frac{Post}{Pre}$
Panel A: LPC Data									
Hodrick-Prescott	2.42	1.41	0.58	1.95	1.66	0.80	1.61	1.38	0.85
CF-Bandpass	2.33	1.36	0.58	1.88	1.46	0.78	1.53	1.14	0.74
4-Quarter Growth Rate	0.94	0.59	0.63	0.71	0.60	0.85	0.60	0.50	0.84
Panel B: KLEMS Data									
Hodrick-Prescott	1.68	0.94	0.56	1.59	1.18	0.74	1.38	0.91	0.66
CF-Bandpass	1.65	1.02	0.62	1.56	1.13	0.72	1.34	0.85	0.63
Annual Growth Rate	2.73	1.89	0.69	2.28	1.91	0.84	1.99	1.63	0.82

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

Dataset & Filter	$\frac{s.d.(Hours)}{s.d.(Output)}$ Pre-1983	$\frac{s.d.(Hours)}{s.d.(Output)}$ Post-1984	$\frac{s.d.(Hours)}{s.d.(Output)}$ $\frac{Post}{Pre}$	$\frac{s.d.(Employment)}{s.d.(Output)}$ Pre-1983	$\frac{s.d.(Employment)}{s.d.(Output)}$ Post-1984	$\frac{s.d.(Employment)}{s.d.(Output)}$ $\frac{Post}{Pre}$	$\frac{s.d.(Employment)}{s.d.(Hours/Worker)}$ Pre-1983	$\frac{s.d.(Employment)}{s.d.(Hours/Worker)}$ Post-1984	$\frac{s.d.(Employment)}{s.d.(Hours/Worker)}$ $\frac{Post}{Pre}$
Panel A: LPC Data									
Hodrick-Prescott	0.80	1.18	1.47	0.67	0.98	1.46	2.99	3.17	1.06
CF-Bandpass	0.81	1.08	1.33	0.66	0.84	1.28	3.13	2.71	0.87
4-Quarter Growth Rate	0.76	1.02	1.35	0.64	0.85	1.34	2.82	3.14	1.11
Panel B: KLEMS Data									
Hodrick-Prescott	0.95	1.26	1.33	0.82	0.97	1.19	3.50	2.73	0.78
CF-Bandpass	0.95	1.11	1.17	0.82	0.83	1.02	3.28	2.47	0.75
Annual Growth Rate	0.83	1.01	1.22	0.73	0.86	1.19	3.24	3.47	1.07

A.2 Measurement of Factor Utilization Rate

Basu, Fernald and Kimball (2006) estimate industry-level production functions of the form $Y = Z.F\left[(A.K)^{\alpha_K}(E.H.N)^{\alpha_L}, M\right]$, where Z indexes technology, and Y is the industry-level gross output produced using capital stock K (with utilization rate A), employees N (each of whom work for H hours and puts in effort level E), and intermediate inputs of energy and materials M. In doing so, they use changes in hours per worker H as a proxy that is proportional to unobserved changes in both labour effort E and capital utilization A. This methodology is valid under the following assumptions:

1. Firms minimize cost, given that the function $F(.)$ is monotonically increasing.
2. Firms are price-takers in factor markets but no assumption is required about firms' product-pricing and the goods market structure.
3. Firms face adjustment costs to investment and hiring, so that capital and employment are both quasi-fixed.

This framework yields the following estimating equation for each industry:

$$dy = \beta_1.dx + \beta_2.dh + dz$$

where dy is the growth rate of output, and dx is a vector of the growth rates of observed factors of production K, N and M. The specification controls for both labour and capital utilization changes through the growth in hours-per-worker dh, and the residuals dz are interpreted as the utilization-adjusted technological change.

Fernald (2014) publishes and regularly updates a factor utilization growth rate series and a utilization-adjusted total factor productivity growth series for the aggregate U.S. economy based on the above framework, and that is what I have used in this paper. As a robustness check, I verify in Table A.4 that the capacity utilization rate of the aggregate U.S. economy, based on a survey of plants by the Census Bureau, is highly correlated with Fernald's factor utilization rate and the changes in their business cycle moments around 1983-84 are also comparable. While the two utilization rates are measured quite differently, it is comforting to note that their properties are similar as a proxy for the intensive margin of factor use.

Table A.4: Business Cycle Moments of Factor & Capacity Utilization Rates

	Correlation with Output			**Correlation with Hours**			**Variance**		
Utilization Rates	1969-1983	1984-2017	Change	1969-1983	1984-2017	Change	1969-1983	1984-2017	Change
Factor Utilization	0.75	0.50	-0.25	0.75	0.52	-0.23	18.46	4.48	-75.7%
Capacity Utilization	0.86	0.61	-0.25	0.89	0.64	-0.25	68.53	22.49	-67.2%

Note: Quarterly growth rate is used to filter all the variables. The factor utilization rate is from Fernald (2014). The capacity utilization rate is sourced from FRB based on QSPC by the Census Bureau, which asks plants to report both their current production and their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". The correlation between the growth rates of factor utilization and capacity utilization rates is 0.74.

Kurmann and Sims (2021) find that revisions to the Fernald measure of factor utilization rate after 2007 has led to a significant change in the cyclical properties of the factor utilization rate series and the utilization-adjusted TFP series. Focussing on arguably uncontroversial data before 2007 does not change the results in this paper as the key change studied here is in the mid-1980s. This is the reason why, in Table 2.1, I study the changes in the cyclical properties of the Fernald series for 20 years around 1983-84, starting from 1964 and ending in 2003.

Fernald (2014) provides data for U.S. business sector TFP and its components in quarterly and annual growth rates. Unless one makes an arbitrary normalization of the growth rates to a specific year to calculate the series in levels, it is not possible to study the cyclical properties of the data series using other de-trending methods like the HP filter or bandpass filters. Ramey (2016) provides such a level data series, making the following normalization: log TFP is zero in first quarter of 1947. In Table A.5, I use this version of level data from Ramey (2016) to check robustness of relevant business cycle moments. It is clear that the changes in the procyclicality of utilization-adjusted TFP is somewhat sensitive to the choice of de-trending method. However, this is not important for my main argument in the paper. What is crucial is that, irrespective of the filter choice, (a) factor utilization is always more procyclical than utilization-adjusted TFP, and (b) the relative importance of factor utilization in the variance of aggregate TFP has dropped in the post-1984 era.

Table A.5: Business Cycle Moments of Components of TFP

	Correlation with Output			**Correlation with Hours**			**Variance**	
Components of TFP & Filter Choice	Pre-1983	Post-1984	Change	Pre-1983	Post-1984	Change	Pre-1983	Post-1984
Panel A: TFP								
Hodrick-Prescott	0.89	0.61	-0.28	0.61	0.16	-0.45	25.4 (100%)	6.1 (100%)
BK-Bandpass	0.88	0.59	-0.29	0.60	0.15	-0.45	22.7 (100%)	5.0 (100%)
CF-Bandpass	0.89	0.69	-0.20	0.62	0.25	-0.36	23.8 (100%)	7.8 (100%)
Quarterly Growth Rate	0.89	0.65	-0.24	0.44	-0.08	-0.52	8.8 (100%)	3.7 (100%)
Panel B: Factor Utilization Rate								
Hodrick-Prescott	0.82	0.65	-0.17	0.72	0.51	-0.21	19.7 (77.6%)	3.6 (59.0%)
BK-Bandpass	0.86	0.64	-0.22	0.74	0.53	-0.22	18.1 (79.7%)	2.9 (58.0%)
CF-Bandpass	0.86	0.79	-0.07	0.76	0.62	-0.14	18.7 (79.0%)	5.5 (71.8%)
Quarterly Growth Rate	0.63	0.43	-0.20	0.72	0.43	-0.28	5.2 (59.1%)	0.6 (16.2%)
Panel C: Utilization-Adjusted TFP								
Hodrick-Prescott	0.12	-0.13	-0.24	-0.16	-0.40	-0.24	5.7 (22.4%)	2.5 (41.0%)
BK-Bandpass	0.07	-0.14	-0.21	-0.22	-0.42	-0.20	4.6 (20.3%)	2.1 (42.0%)
CF-Bandpass	0.11	-0.16	-0.26	-0.19	-0.49	-0.30	5.0 (21.0%)	2.2 (28.2%)
Quarterly Growth Rate	0.18	0.24	+0.06	-0.35	-0.37	-0.02	3.6 (40.9%)	3.1 (83.8%)

In the context of measuring the intensive margin of labour effort through the hours per worker variable, the robustness of one particular cyclical moment deserves special mention, namely, the volatility of employment relative to that of hours per worker. As seen in Table A.3, the change in the ratio of standard deviations of employment and hours per worker is not robust to either the choice of the dataset or the filtering process. For some of these choices, the relative volatility measure shows an increase in the post-1984 period, while for others it shows a decline. This is despite a clear and unambiguous increase in the relative volatility of employment with respect to the factor utilization rate. Since Fernald (2014) uses hours per worker to create the factor utilization rate series, this discrepancy in their moments is somewhat puzzling. However, this has been addressed in Wang (2014). She argues that while factor utilization is proportional to hours per worker, the constant of proportionality is higher for manufacturing than services. Thus, a changing sectoral composition of the economy towards services can explain the discrepancy between the aggregate properties of the two variables.

A.3 SVAR Specification and Impulse Response Functions

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.[18] 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.[19] 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 differencing 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 use the technique in Galí and Gambetti (2009) 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 $x_t \equiv [\Delta (y_t - h_t), h_t]$, where y_t and h_t denote the per capita log output and per capita log hours, the reduced form VAR can be written as:

$$x_t = A_{0,t} + A_{1,t}x_{t-1} + A_{2,t}x_{t-2} + ... + A_{p,t}x_{t-p} + u_t \tag{A.1}$$

where $A_{0,t}$ is a vector of time-varying intercepts, $A_{i,t}$, $i = 1, ..., p$ 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.1) 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 hours also generates a negative response of hours to a positive technology shock in the pre-

[18] 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, $\begin{pmatrix} \Delta (y_t - h_t) \\ h_t \end{pmatrix} = \begin{pmatrix} C_{11}(L) & 0 \\ C_{21}(L) & C_{22}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_t^a \\ \varepsilon_t^\nu \end{pmatrix}$, where ε_t^a is the technology shock, and ε_t^ν is the non-technology or demand shock.

[19] There were other criticisms as well. For example, 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 et al. (2014) provide a flexible finite-horizon alternative to the long-run restrictions, and corroborate Galí's conclusions.

1980 period (see panel (a) of Figure A.2).

Chang and Hong (2006) criticize the use of ALP as the measure of productivity in the above SVAR. They argue that using ALP 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 ALP with TFP in Figure A.3.

As an alternative to VAR specifications, I present results from a local projections analysis à la Jorda (2005) that estimates the impulse response of hours to changes in utilization-adjusted TFP. I use the specification in Ramey (2016):

$$\ln\left(hours_t/pop_t\right) = \alpha_j + \beta_j \Delta \ln\left(uatfp_t\right) + \theta_j\left(L\right) X_{t-1} + \varepsilon_{t+j} \tag{A.2}$$

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

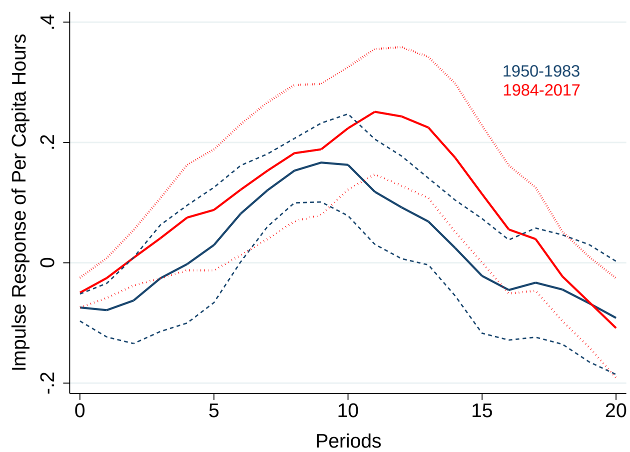
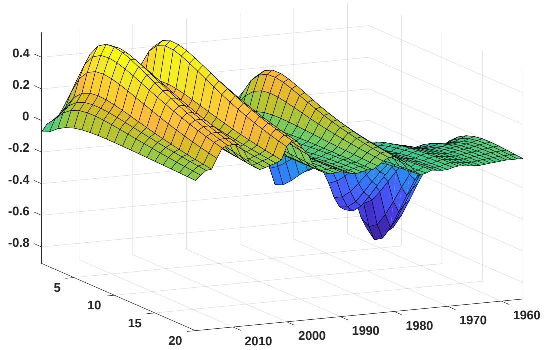


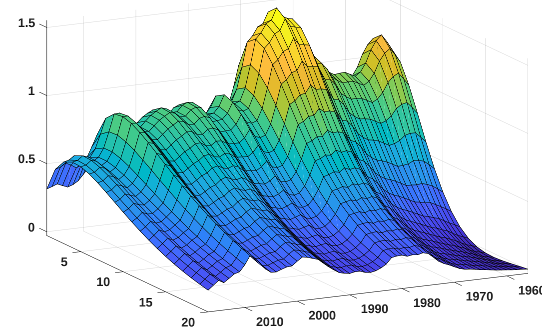
Figure A.1: IRF of Per Capita Hours to Utilization-Adjusted TFP Shock

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).

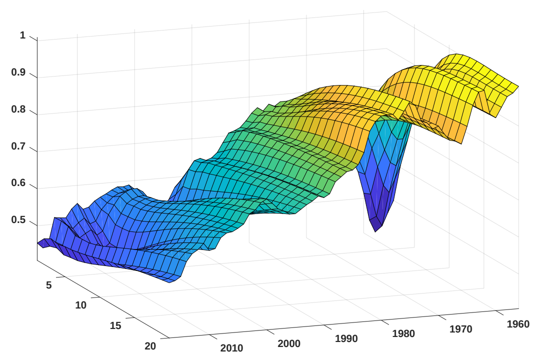
This methodology of a simple regression model with the shock being the explanatory variable not only shows the negative correlation of hours and technology shock but also that the negative response of hours became muted after the mid-1980s (see Figure A.1), probably due to a more accommodative monetary policy (see Galí, López-Salido and Vallés (2003)). This muted negative response of hours to a positive technology shock increases the productivity correlation with labour input (see the blue dashed line in Figure 2.4) and acts as a counter-force to the vanishing procyclicality of productivity with labour input.



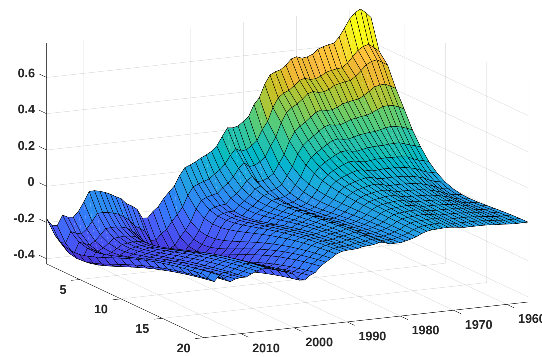
(a) Technology Shock: Hours



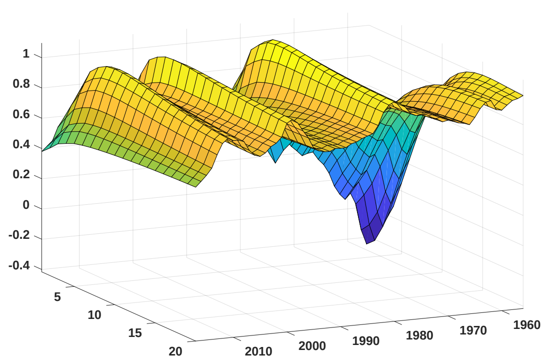
(b) Demand Shock: Hours



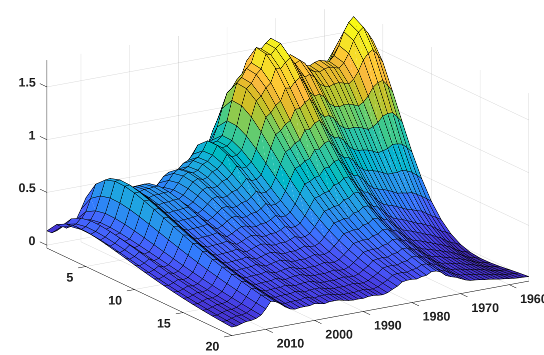
(c) Technology Shock: Labour Productivity



(d) Demand Shock: Labour Productivity



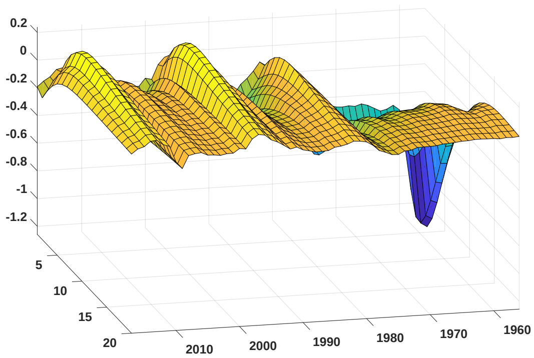
(e) Technology Shock: Output



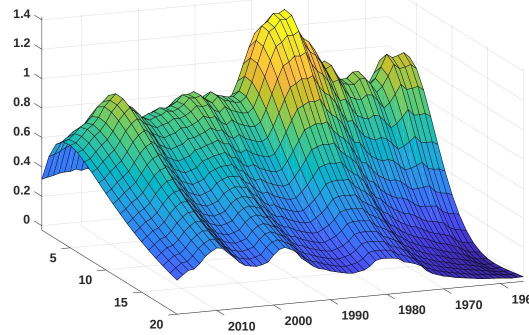
(f) Demand Shock: Output

Figure A.2: Dynamic Impulse Responses to Technology & Demand Shocks

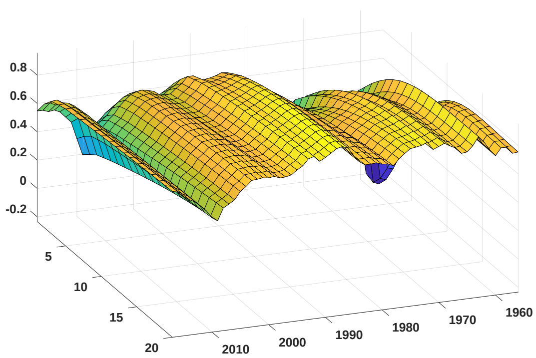
Note: Impulse Response Functions of per-capita hours, labour productivity and per-capita output from a 2-variable (viz., labour productivity growth and per-capita hours) time-varying long-run SVAR. Data is sourced from the BLS-LPC quarterly dataset for the U.S. business sector. Quarterly civilian non-institutional population data is from the Employment Situation release of the BLS.



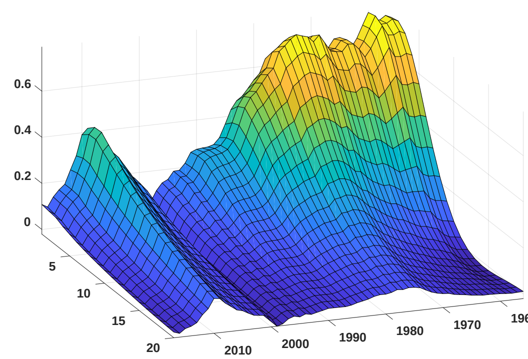
(a) Technology Shock: Hours



(b) Demand Shock: Hours



(c) Technology Shock: TFP



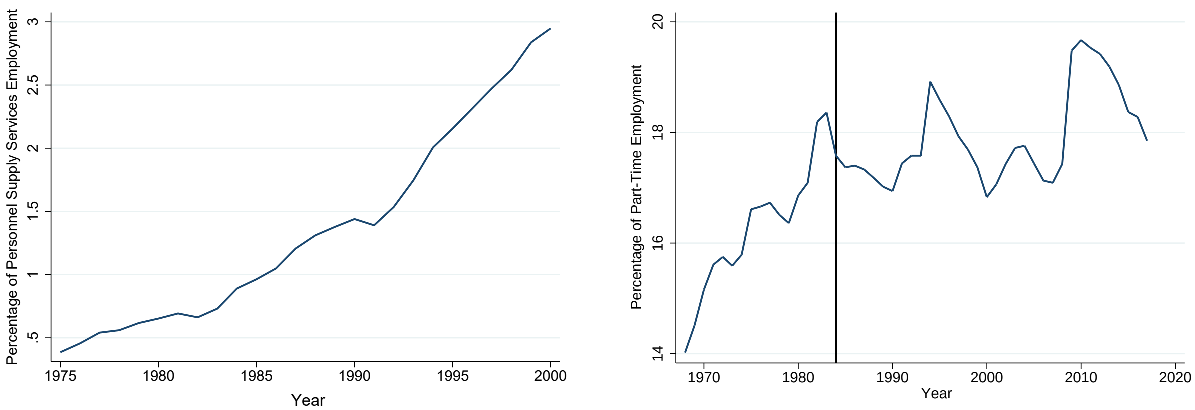
(d) Demand Shock: TFP

Figure A.3: Dynamic Impulse Responses to Technology & Demand Shocks

Note: Impulse Response Functions 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 for the U.S. business sector, and quarterly civilian non-institutional population data is from the Employment Situation release of the BLS.

A.4 Plausible Channels of Increased Labour Market Flexibility in the U.S.

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.



(a) Personnel Supply Services Employment Share

(b) Part-time Employment Share

Figure A.4: Employment Shares of Personnel Supply Services and Part-time Jobs in the U.S.
Note: Data on Personnel Supply Services sector employment share between 1975 and 2000 is sourced from the Quarterly Census of Employment and Wages (QCEW) of the BLS. Personnel Supply Services sector is identified as the 3-digit Standard Industrial Classification (SIC) industry-code of 736. Data on part-time employment, defined as less than 35 hours of work per week, is sourced from Labor Force Statistics (LFS) of the Current Population Survey (CPS) for the period between 1968 and 2017.

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 (2023) also study the implications of a similar 2001-reform of lifting constraints on employment of temporary contract workers in Italy. However, 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, using data from the Quarterly Census of Employment and Wages (QCEW) I do not find any noticeable acceleration in the trend growth of employment share of the personnel supply service industry around the mid-1980s (see Figure A.4a). Even focussing on the private sector only, the average annual growth in personnel supply services sector employment was 9.3% between 1975 and 1983, 9.9% between 1984 and 1990 and 7.1% between 1991 and 2000. Moreover, 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. In Figure A.4b, I study the time series of the share of part-time workers in total employment using CPS data, and do not find any noticeable upsurge, if not an actual plateauing, in the share of part-time workers around the mid-1980s, identified by the vertical line at 1984.

Galí and van Rens (2021) 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 of 24% in the gross job destruction rate, firms need to hire fewer new workers to maintain the level of employment. This reduced hiring activity implies a lower cost of employment adjustment in equilibrium, thereby leading to more countercyclical productivity. However, looking at job flow data from Shimer (2012), I do not find any substantial drop in the job separation rate around 1983. Table A.6 shows the average job flow rates for the U.S. for the pre and post-1984 periods using Shimer's data, and it is evident that the drop in labour market turnover is not large enough to cause the dramatic decline in cyclical productivity correlations around that time.

Table A.6: Job Flows for the U.S. Economy (1948-2006)

Job Flows	**1948-1983**	**1984-2006**	**Change**
Job Separation Rate, s	3.51%	3.32%	-5.57%
Job Finding Rate, f	47.03%	43.06%	-8.81%
Gross Separation Rate, $s/(1-f)$	6.68%	5.88%	-12.75%

Note: Quarterly job flow data is sourced from Shimer (2012).

A.5 International Evidence

In Table A.7, 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 average labour productivity with total hours worked, and (iii) relative volatility of employment to output. Variables capturing labour market structure are changes in (i) union density, (ii) employment protection laws as measured by the OECD EPRC index, and (ii) gross job separation rate. The countries are arranged in ascending order of the change in union density.

Table A.7: Labour Market Statistics from OECD Countries

	$\triangle$Corr.(ALP,x)		**$\triangle \frac{\text{S.D.(Employment)}}{\text{S.D.(Output)}}$**	**Labour Market Structure**		
Country	**x=Output**	**x=Hours**		**$\triangle$Union Density**	**$\triangle$EPRC**	**$\triangle$Separation Rate**
France	-0.13	0.17	26%	-54%	+1%	0%
U.S.A.	**-0.54**	**-0.62**	**32%**	**-49%**	**0%**	**-24%**
Australia	-0.44	-0.48	73%	-37%	+21%	+4%
Austria	-0.21	-0.16	-16%	-32%	-11%	No data
U.K.	-0.39	-0.46	41%	-28%	+16%	+11%
Spain	-1.37	-0.74	317%	-24%	-34%	-1%
Germany	-0.04	-0.52	-10%	-24%	+8%	+41%
Ireland	-0.44	-0.21	44%	-21%	-2%	-44%
Italy	-0.09	-0.16	71%	-4%	0%	+11%
Norway	-0.35	-0.12	47%	-3%	0%	+47%
Canada	0.01	0.09	-22%	+2%	0%	+9%
Sweden	0.01	-0.03	59%	+10%	-7%	+84%
Finland	-0.25	0.21	-9%	+36%	-22%	No data

Note: All time changes, denoted by Δ, are between the post and pre-1984 periods, except for EPRC and the job separation rate since internationally comparable data on job flows and EPRC are not available before the 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 Sahin (2015). The EPRC index measures the strength of employment protection legislations and is sourced from OECD database from 1985 to 2013. The index is very persistent over time, so changing the end year of the sample would make very little difference. Union density data are sourced from *OECD Annual Trade Union Density Dataset*. ALP is defined as real GDP per hour worked. Quarterly data on output, employment and total 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*. HP-filtered variables are used to calculate the changes in cyclical correlations and relative volatility.

The international evidence in Table A.7 does not support the decrease in job separation rate as a common cause for reduced procyclicality of productivity across countries. Of the 12 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 countries essentially refutes the claim that changes in job separation rate is a significant determinant of changes in productivity correlations.

The index of employment protection regulations published by the OECD is very persistent over time for any country. Hence it is hard to explain changes in fast-moving business cycle moments changes through that index. One would expect more negative changes in that index to be consistent with higher relative volatility of employment, but the international data presented in Table A.7 does not provide enough proof of that.

De-unionisation is one labour market feature strongly correlated with business cycle movements across OECD countries. In Figure 2.10, I show that a de-unionization episode strongly predicts a drop in the cyclical correlation of productivity with labour input. In fact, in countries like Canada, Finland and Sweden, where union membership rates did not decline, there was no loss in procyclicality of productivity.

A.6 Cross-industry Evidence: 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. I follow a difference-in-difference regression strategy similar to Card (1992) to argue for this causal channel. I consider a very simple structural model that explains the fall in employment adjustment cost in industry i, $\Delta Cost_i$, as a function of the fraction of workers unionized in the industry prior to mid-1980s, $Union_i^{pre}$, and the change in correlation of labour productivity with hours worked, $\Delta Corr\,(alp_i, h_i)$, as a function of that change in cost:

$$\Delta Cost_i = a + bUnion_i^{pre} + e_i \tag{A.3}$$

$$\Delta Corr\,(alp_i, h_i) = \alpha + \beta \Delta Cost_i + \varepsilon_i \tag{A.4}$$

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

$$\begin{aligned} \Delta Corr\,(alp_i, h_i) &= (\alpha + a\beta) + b\beta Union_i^{pre} + (\beta e_i + \varepsilon_i) \\ \Longrightarrow \Delta Corr\,(alp_i, h_i) &\equiv \beta_0 + \beta_1 Union_i^{pre} + \eta_i \end{aligned} \tag{A.5}$$

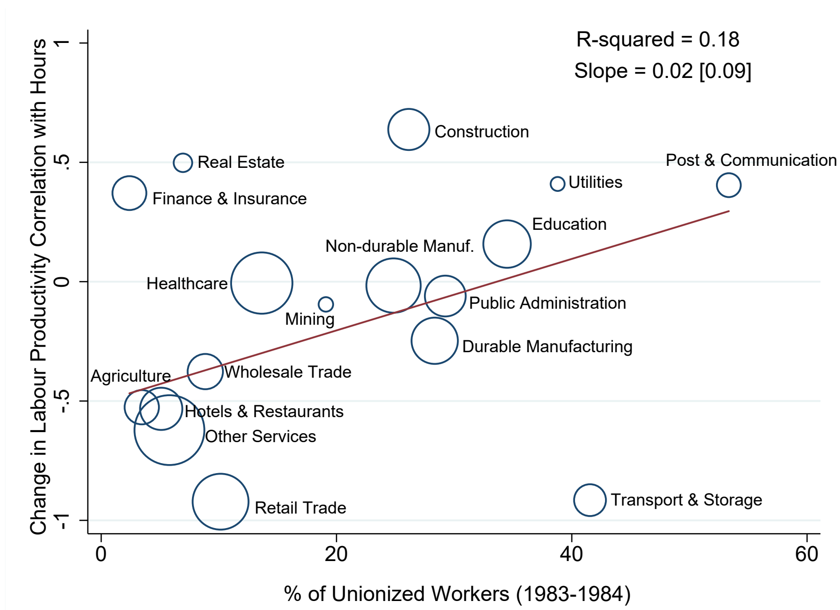


Figure A.5: Effect of Union Density on Productivity Correlation

Note: Data on industry-level unionization rates comes from the CPS, collected by Hirsch and Macpherson (2003). 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.5) 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.5) 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.5. I weighted the observations by the pre-1983 average industry employment level to avoid small industries driving the correlation pattern.

Finally, replacing the change in productivity correlations by the change in the relative volatility of employment in equation (A.5), 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. This is shown in Figure A.6.

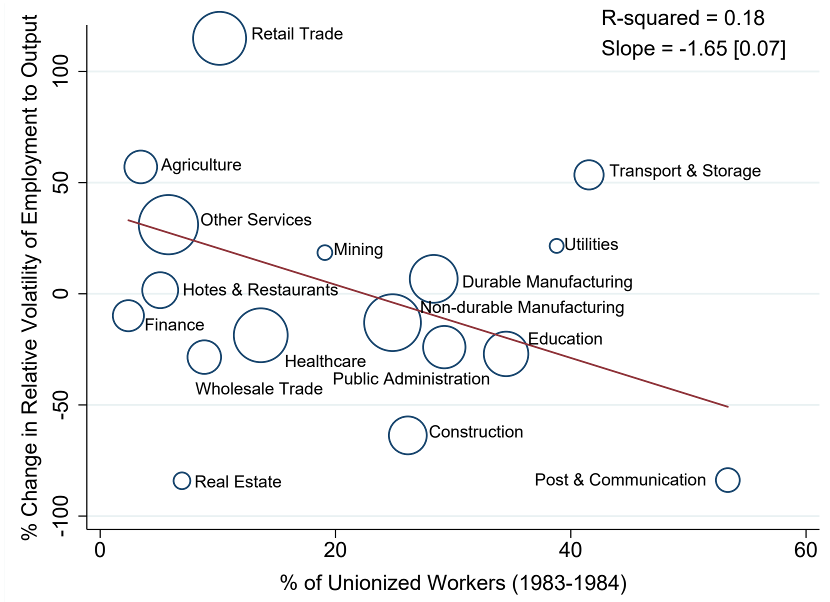
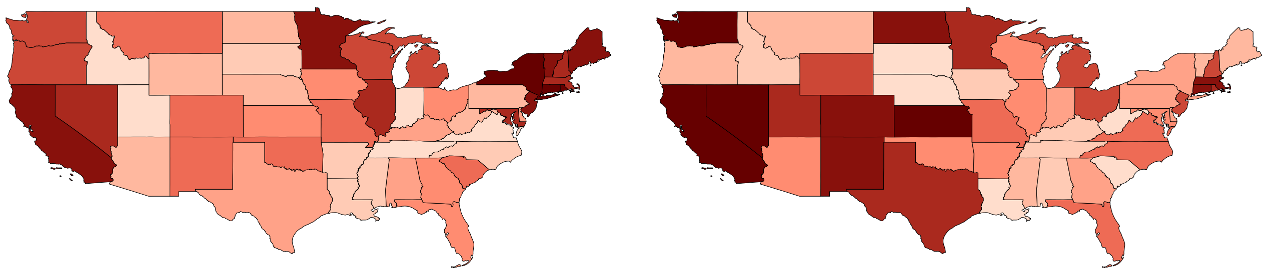


Figure A.6: Effect of Union Density on Relative Volatility of Employment

Note: Data on industry-level unionization rates comes from the CPS, collected by Hirsch and Macpherson (2003). 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.

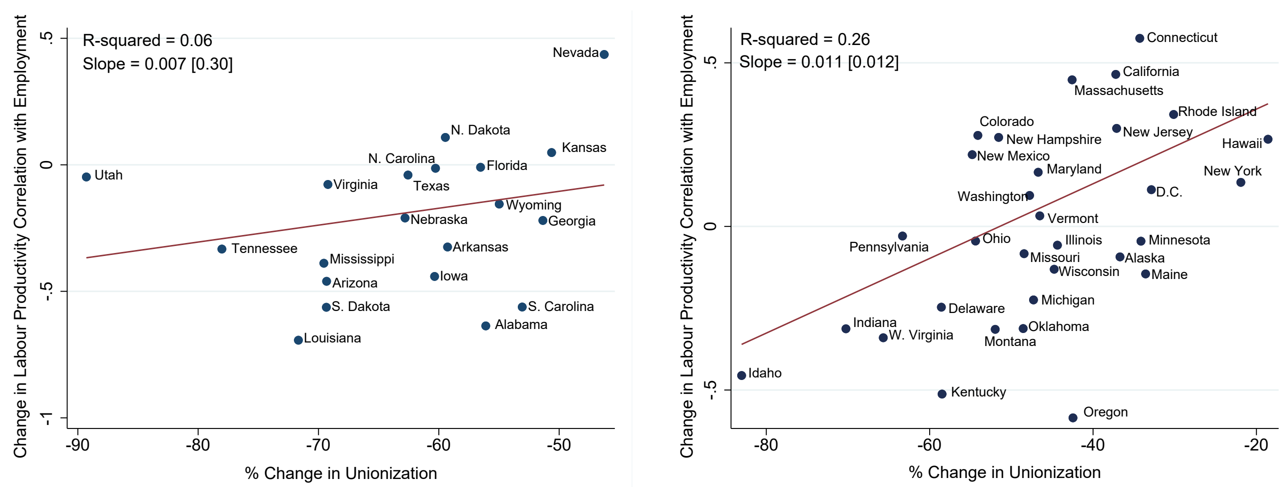
A.7 Evidence for De-unionization across U.S. States

The following two maps of mainland U.S. in Figure A.7 group 49 U.S. states (the states of Alaska and Hawaii are missing) into deciles, according to (a) the percentage change in unionization between the average union densities in the pre and post-1984 periods, and (b) the change in correlation between employment growth and output per worker growth in the pre and post-1984 periods.



(a) De-unionization (b) Productivity Puzzle

Figure A.7: De-unionization & Vanishing Procyclicality of Productivity in U.S. States
Note: Lighter shades correspond to a larger percentage decline in union density in panel (a), and to a larger decrease in labour productivity correlation with employment in panel (b).



(a) Right-to-Work States (b) Non Right-to-Work States

Figure A.8: Right-to-Work Status and the Role of De-unionization for the Productivity Puzzle
Note: Categorization of states into *Right-to-Work* and *Non Right-to-Work* has been done based on the status in 1984. See notes to Figure 2.7 for details regarding data sources and analyses. Although observation for each state is weighed by its average employment level, to improve readability of the names of the states in the two categories I have not shown the weights using bubbles.

B Appendix to Section 3

B.1 System of equilibrium conditions

I consider a recursive steady-state with no inflation, unit GDP, unit effort per hour and unit hour per worker: $\bar{\pi} = \bar{y} = \bar{e} = \bar{h} = 1$.

$$w_t h_t = \left[\mathcal{N} n_t^{\eta} + \frac{\mathcal{H}}{1+\gamma} h_t^{1+\gamma} + \frac{\mathcal{E}}{1+\tau} e_t^{1+\tau} h_t\right] c_t \tag{B.1}$$

$$y_t = a_t \left(e_t h_t n_t\right)^{1-\alpha} - g_t \tag{B.2}$$

$$\frac{w_t h_t}{\Omega_t} = (1-\alpha)\frac{y_t + g_t}{n_t} - g_t' + E_t\left(\Lambda_{t,t+1} g_{t+1}'\right) \tag{B.3}$$

$$e_t = \left[\frac{1+\tau}{\tau}\frac{\mathcal{H}}{\mathcal{E}}\right]^{\frac{1}{1+\tau}} h_t^{\frac{\gamma}{1+\tau}} \tag{B.4}$$

$$\left(\frac{1+\gamma+\tau}{\tau}\right)\mathcal{H} n_t h_t^{\gamma} c_t = (1-\alpha)\left(1+\frac{\gamma}{1+\tau}\right)\left[1-\frac{\phi_p}{2}\left(\pi_t - 1\right)^2\right]\frac{y_t + g_t}{h_t} \tag{B.5}$$

$$c_t + \nu_t = \left[1 - \frac{\phi_p}{2}\left(\pi_t - 1\right)^2\right] y_t \tag{B.6}$$

$$\Lambda_{t-1,t} = \beta\frac{c_{t-1}}{c_t} \tag{B.7}$$

$$R_t E_t\left(\frac{\Lambda_{t,t+1}}{\pi_{t+1}}\right) = 1 \tag{B.8}$$

$$(1-\varepsilon) + \varepsilon\Omega_t = \phi_p\left(\pi_t - 1\right)\pi_t - \phi_p E_t\left[\Lambda_{t,t+1}\left(\pi_{t+1} - 1\right)\pi_{t+1}\frac{y_{t+1}}{y_t}\right] \tag{B.9}$$

$$R_t/\bar{R} = \left(\pi_t/\bar{\pi}\right)^{\psi_\pi} \tag{B.10}$$

$$\ln a_t = \rho_a \ln a_{t-1} + \epsilon_t^a \tag{B.11}$$

$$\ln \nu_t = (1-\rho_\nu)\ln\bar{\nu} + \rho_\nu \ln \nu_{t-1} + \epsilon_t^{\nu} \tag{B.12}$$

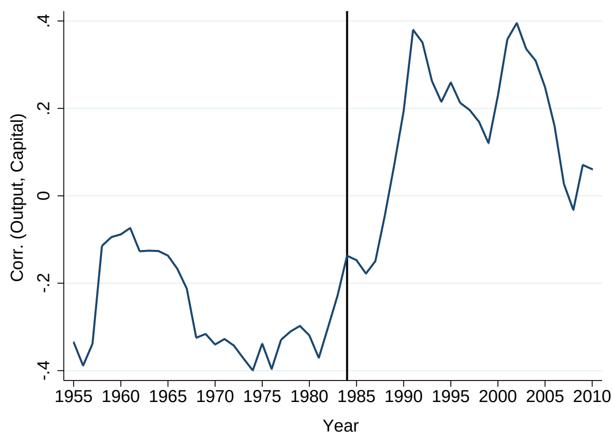
$$g_t = \begin{cases} \frac{\phi_n}{2}\left(n_t - n_{t-1}\right)^2 & \text{for employment adjustment cost} \\ \frac{\phi_f}{2}\left[\left(n_{t-1} - n_t\right) + \sqrt{\left(n_{t-1} - n_t\right)^2 + \kappa}\right] & \text{for firing cost} \end{cases} \tag{B.13}$$

$$g_t' = \begin{cases} \phi_n\left(n_t - n_{t-1}\right) & \text{for employment adjustment cost} \\ -\frac{\phi_f}{2}\left[1 + \frac{n_{t-1} - n_t}{\sqrt{\left(n_{t-1} - n_t\right)^2 + \kappa}}\right] & \text{for firing cost} \end{cases} \tag{B.14}$$

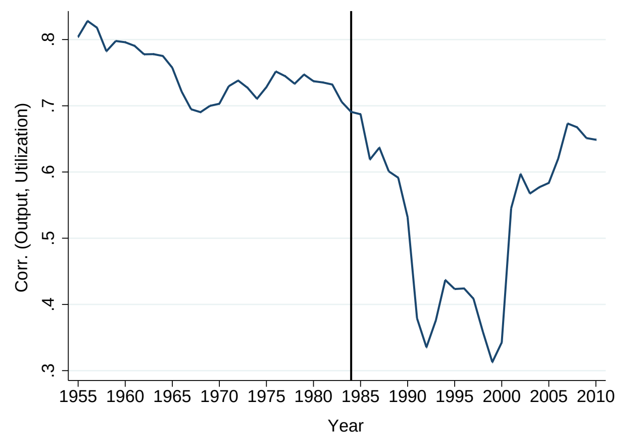
For the firing cost case, one can ignore the steady-state value of the cost, $\frac{\phi_f}{2}\sqrt{\kappa}$ being small enough, since $\kappa = 0.001$ and $\phi_f < 0.20$ in our estimation. Otherwise, one can re-define the cost function g_t as the deviation from its positive steady-state value. All results are identical under either treatment. Note that while a smaller value of κ makes the approximation of the firing cost function better, it makes g_t' closer to negative infinity in the steady state. Thus, a balance needs to be struck in the choice of κ.

B.2 Cyclical Moments of Capital and Factor Utilization

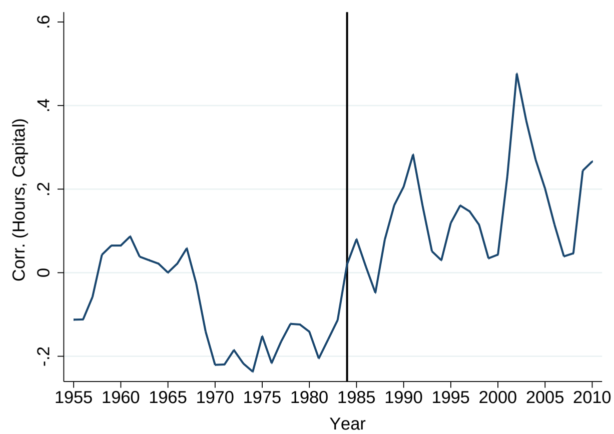
The model in this paper does not feature capital, rather includes only employment and effort. Since labour effort is not directly measurable in the data, one concern is that whatever is being labelled as 'effort' in the model is essentially capital, the missing factor of production. Therefore, it is 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.



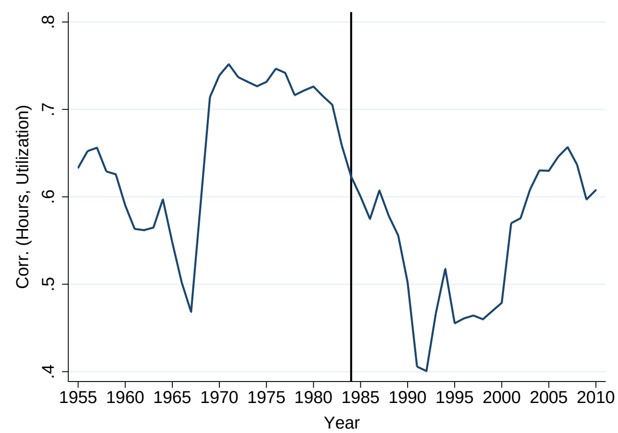
(a) Corr.(Output,Capital)



(b) Corr.(Output,Utilization)



(c) Corr.(Hours,Capital)

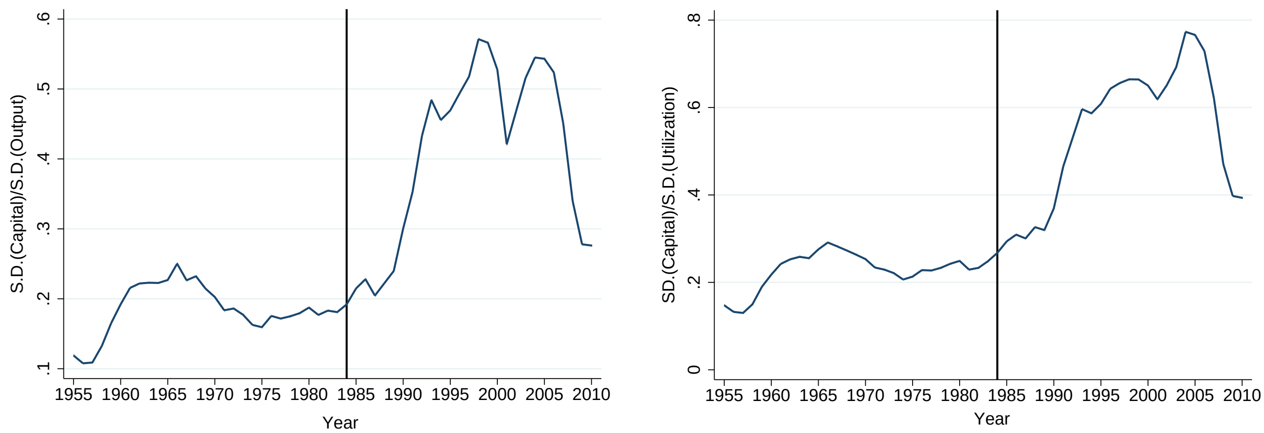


(d) Corr.(Hours,Utilization)

Figure B.1: 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.

Looking at panels (b) and (d) in Figure B.1, 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 B.1 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 (2) of Table 4.2), correlation of effort with labour productivity fell by 0.15, which is qualitatively similar to that of factor utilization and not capital.



(a) $\frac{\text{s.d.(Capital)}}{\text{s.d.(Output)}}$ (b) $\frac{\text{s.d.(Capital)}}{\text{s.d.(Utilization)}}$

Figure B.2: 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.

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.

C Appendix to Section 4

C.1 Business Cycle Moments in Levels

Table C.1: Empirical and Model-Implied Business Cycle Moments

Business Cycle Moments	**Pre-1984**		**Post-1984**				
	Data (1)	**Model** (2)	**Data** (3)	ϕ_n (4)	ϕ_p (5)	ψ_π (6)	σ_a, σ_ν (7)
I. Labour Productivity Correlations							
A. Unconditional Moments							
Output: $Corr\ (y_t, alp_t)$	0.56	0.28	-0.04	-0.10	0.15	0.62	0.32
Hours: $Corr\ (n_t h_t, alp_t)$	0.12	-0.13	-0.54	-0.49	-0.28	0.31	-0.16
Employment: $Corr\ (n_t, alp_t)$	0.01	-0.46	-0.59	-0.68	-0.56	-0.09	-0.45
Hours Per Worker: $Corr\ (h_t, alp_t)$	0.40	0.40	-0.20	0.26	0.38	0.54	0.36
Effort: $Corr\ (e_t, alp_t)$	0.53	0.40	0.00	0.26	0.38	0.54	0.36
B. Conditional on Technology Shock							
Output: $Corr\ (y_t, alp_t)$	0.69	0.96	0.89	0.94	0.95	0.99	-
Hours: $Corr\ (n_t h_t, alp_t)$	-0.66	-0.86	-0.73	-0.92	-0.87	-0.86	-
C. Conditional on Demand Shock							
Output: $Corr\ (y_t, alp_t)$	0.80	0.18	-0.41	-0.40	-0.01	0.72	-
Hours: $Corr\ (n_t h_t, alp_t)$	0.67	-0.08	-0.57	-0.61	-0.29	0.57	-
II. Absolute & Relative Volatilities							
Output: $s.d.\ (y_t)$	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Employment: $s.d.\ (n_t)$	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Employment to Output: $s.d.\ (n_t) / s.d.\ (y_t)$	0.70	0.70*	0.97	0.97*	0.81	0.41	0.70

Note: All columns report moments of BK bandpass filtered (between 6 and 32 quarters) log variables. ALP is defined as output per hour worked. Factor utilization rate from Ramey (2016) based on Fernald (2014) is used to measure effort in data. The data moments reported for productivity correlations conditional on technology and demand shocks are taken from Table 5 of Galí and Gambetti (2009). Columns (1) and (3) report the empirically observed business cycle moments between 1956 and 1983 and between 1984 and 2011, respectively. Column (2) reports the model simulated moments using the pre-1984 parameter values noted in Table 4.1. Columns (4) through (7) report the model-implied moments when each parameter is changed from their pre-1984 to post-1984 values according to Table 4.1.

C.2 Robustness to Calibration of Labour Supply Elasticities

Table C.2: Robustness to Choice of γ and τ

Business Cycle Moments		**Changes in Moments due to Decline in ϕ_n**	
	Data (1)	Baseline: $(\gamma, \tau) = (2.00, 0.60)$ (2)	$(\gamma, \tau) = (3.20, 0.74) \rightarrow (0.80, 0.60)$ (3)
I. Labour Productivity Correlations			
A. Unconditional Moments			
Output: $Corr\,(y_t, alp_t)$	-0.61	-0.38	-0.73
Hours: $Corr\,(n_t h_t, alp_t)$	-0.65	-0.36	-0.60
Employment: $Corr\,(n_t, alp_t)$	-0.60	-0.22	-0.54
Hours Per Worker: $Corr\,(h_t, alp_t)$	-0.60	-0.15	-0.45
Effort: $Corr\,(e_t, alp_t)$	-0.53	-0.15	-0.45
B. Conditional on Technology Shock			
Output: $Corr\,(y_t, alp_t)$	+0.19	-0.02	-0.04
Hours: $Corr\,(n_t h_t, alp_t)$	-0.06	-0.06	-0.02
C. Conditional on Demand Shock			
Output: $Corr\,(y_t, alp_t)$	-1.21	-0.58	-1.05
Hours: $Corr\,(n_t h_t, alp_t)$	-1.24	-0.52	-0.88
II. Absolute & Relative Volatilities			
Output: $s.d.\,(y_t)$	-36%	+5%	+14%
Employment: $s.d.\,(n_t)$	-12%	+45%	+57%
Employment to Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+39%	+39%*	+39%*

Note: Columns (1) and (2) are the same as those in Table 4.2. Column (3) uses the values of 3.20 and 0.74 for γ and τ, respectively in the pre-1984 calibration. This yields a value of 3.28 for ϕ_n in the pre-1983 period. For the post-1984 calibration, column (3) uses 0.80 and 0.60 as the values for γ and τ, respectively, yielding 1.31 as the value of ϕ_n.

C.3 Quantitative Performance of Firing Cost Model

Table C.3: Changes in Business Cycle Moments between Pre and Post-1984: Firing Cost Model

Business Cycle Moments	**Data** (1)	**Changes in Moments between Pre & Post-1984 due to Parameter Changes — Model** **Union:** ϕ_f (2)	**Nominal Rigidity:** ϕ_p (3)	**Monetary Policy:** ψ_π (4)	**Shock Volatility:** σ_a,σ_ν (5)
I. Labour Productivity Correlations					
A. Unconditional Moments					
Output: $Corr\left(y_t, alp_t\right)$	-0.61	-0.39	-0.11	+0.31	+0.04
Hours: $Corr\left(n_t h_t, alp_t\right)$	-0.65	-0.37	-0.13	+0.40	-0.03
Employment: $Corr\left(n_t, alp_t\right)$	-0.60	-0.22	-0.10	+0.33	+0.00
Hours Per Worker: $Corr\left(h_t, alp_t\right)$	-0.60	-0.16	-0.01	+0.10	-0.04
Effort: $Corr\left(e_t, alp_t\right)$	-0.53	-0.16	-0.01	+0.10	-0.04
B. Conditional on Technology Shock					
Output: $Corr\left(y_t, alp_t\right)$	+0.19	-0.02	-0.02	+0.03	-
Hours: $Corr\left(n_t h_t, alp_t\right)$	-0.06	-0.07	-0.01	+0.01	-
C. Conditional on Demand Shock					
Output: $Corr\left(y_t, alp_t\right)$	-1.21	-0.59	-0.16	+0.47	-
Hours: $Corr\left(n_t h_t, alp_t\right)$	-1.24	-0.53	-0.18	+0.58	-
II. Absolute & Relative Volatilities					
Output: $s.d.\left(y_t\right)$	-36%	+4%	+1%	-3%	-24%
Employment: $s.d.\left(n_t\right)$	-12%	+43%	+15%	-40%	-24%
Employment to Output: $s.d.\left(n_t\right)/s.d.\left(y_t\right)$	+39%	+39%*	+15%	-38%	+0%

Note: All columns report changes in moments of BK bandpass filtered (between 6 and 32 quarters) log variables between pre and post-1984 periods (1956-1983 and 1984-2011). ALP is defined as output per hour worked. Factor utilization rate from Ramey (2016) based on Fernald (2014) is used to measure effort in data. The data moments reported for productivity correlations conditional on technology and demand shocks are taken from Table 5 of Galí and Gambetti (2009). Column (1) reports the empirically observed changes in the business cycle moments. Columns (2) through (5) show the moment changes due to specific parameter changes in the model simulations. Column (2) reduces the firing cost parameter ϕ_f from 0.17 to 0.08 to match the rise in the volatility of employment relative to that of output (the * marked value of +39%); column (3) changes the Rotemberg price adjustment cost parameter ϕ_p from 8.44 to 11.21 to reflect a higher level of nominal rigidity; column (4) changes the Taylor rule parameter ψ_π from 1.01 to 2.20; and column (5) reduces the shock volatilities σ_a and σ_ν by 5.6% and 25.5% respectively.

D Appendix to Section 5

D.1 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 lower 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.

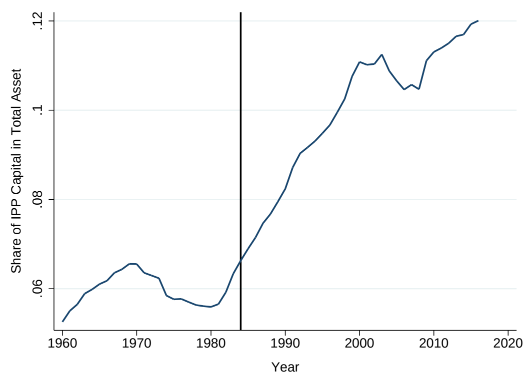


Figure D.1: Share of IPP in Total Non-Residential Capital Stock in the U.S. (1960-2016)

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.

D.2 Relative Importance of Sector-Specific Shocks

Model:
$X_{i,t} = \lambda_i F_t + \varepsilon_{i,t}$; where $X_{i,t}$ is the observed growth rate of value added output or labour input for sector i at time t, F_t is the principal component of sectoral growth rates common to all sectors at time t, and $\varepsilon_{i,t}$ is the 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). Then, $F_t = X_{i,t}\Gamma_1$, where Γ_1 is the first eigenvector in Γ whose columns are sorted according to the ordering of the eigenvalues in Λ. The variance of F_t is interpreted as the aggregate economy-wide volatility (indicated as 'Common' in Tables D.1 and D.2), while that of $\varepsilon_{i,t}$ is the 'Sectoral' variance.

Table D.1: Components of Variance of Value Added Output Growth

	Pre-1983		Post-1984	
Dataset	Common	Sectoral	Common	Sectoral
BEA: 13 Sectors	92.93%	7.07%	68.30%	31.70%
KLEMS: 10 Sectors	48.14%	51.86%	4.42%	95.58%
KLEMS: 31 Sectors	17.96%	82.04%	5.15%	94.85%
IIP: 8 Sectors	94.98%	5.02%	87.21%	12.79%
IIP: 12 Sectors	70.89%	29.11%	31.49%	68.61%
IIP: 20 Sectors	30.63%	69.37%	42.18%	57.82%

Table D.2: Components of Variance of Labour Input Growth

	Pre-1983		Post-1984	
Dataset	Common	Sectoral	Common	Sectoral
CES: 14 Sectors	68.64%	31.36%	44.85%	55.15%
BEA: 13 Sectors	92.31%	7.69%	74.61%	25.39%
KLEMS: 10 Sectors	78.28%	21.72%	50.87%	49.13%
KLEMS: 31 Sectors	89.36%	10.64%	91.14%	8.86%

Garin, Pries and Sims (2018) use the 12-sector-split of the IIP dataset, reported in Table D.1. While that specification shows the drop in the relative importance of the common component in the post-1984 period, an 8-sector-split of IIP shows a much more muted decline and the 20-sector-split shows an increase in importance of the common aggregate shocks. Other datasets and various sectoral splits of them do not reveal a consistent pattern of a significant increase in the relative importance of sector-specific shocks.

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