The Productivity Puzzle and the Decline of Unions

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Abstract

What explains the sudden vanishing of the procyclicality of productivity in the U.S. during the 1980s? Using cross-sectional evidence from states and industries, this paper argues that lower costs of hiring and firing workers due to rapid de-unionization can help explain the productivity puzzle. Lower cost of changing employment prompts firms to rely less on labour hoarding, thereby making productivity less procyclical. In a model with endogenous worker-effort and costly employment adjustment, allowing the hiring cost to decrease by the same amount as the decline in union density can match almost the entire drop in cyclical productivity correlations.

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

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

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1 Introduction

For almost half a century after World War II, average labour productivity (ALP) and total factor productivity (TFP) in the U.S. rose during economic booms and fell in recessions. However, around the mid-1980s, this procyclicality of productivity suddenly vanished. The change in the cyclical correlations of productivity with output and labour input has been well documented and is often referred to as the 'productivity puzzle'.[1] This paper argues that a reduction in hiring frictions posed by a sudden decline in labour union power since the 1980s can help explain the puzzle.

The dominant explanation for procyclical productivity has been the phenomenon of 'labour hoarding', whereby firms, faced with costly hiring and firing, rely on adjusting the effort-level of workers along the business cycle instead of changing employment.[2] Since such changes in the intensity of labour utilization cannot be observed in the changes of actual employment or labour hours, the measured productivity appears to be procyclical.[3] Therefore, a natural explanation for the productivity puzzle is the lower dependence of firms on labour hoarding due to the falling employment adjustment cost.

I employ three ways to test empirically whether firms are indeed relying less on changing labour utilization (intensive margin) and more on employment adjustment (extensive margin) along the business cycle in recent decades. First, the volatility of employment relative to that of output is shown to have risen sharply from around the same time as the reduction in procyclicality of productivity. Second, using a decomposition of the TFP measure by Fernald (2014), I show that the entire loss in procyclicality of TFP has been driven by the loss in procyclicality of the factor utilization component of TFP and not the utilization-adjusted part. Furthermore, after the mid-1980s, procyclical factor utilization accounts for only 28% of the total variation in cyclical TFP, compared to almost 67% in the pre-1980 era. This reduced importance and diminished procyclicality of the intensive margin of factor utilization again point towards factor hoarding becoming less important. Finally, declining frictions in factor markets should be accompanied by changes in how the aggregate U.S. economy responds to different types of shock. For example, in response to a positive demand shock, firms should now increase their labour input by hiring more workers instead of increasing the intensity of labour utilization. This would, in turn, imply that the improvement in measured productivity in response to a positive demand shock will be significantly reduced. Using a time-varying structural vector auto-regression (SVAR) analysis à la Galí and Gambetti (2009), I show that this is indeed the

[1] In popular media, the term 'productivity puzzle' has recently been used in different contexts to mean a variety of phenomena in the U.S. economy, e.g., the slow growth of productivity in recent years, the divergence between labour productivity and real wage growth, etc. However, following McGrattan and Prescott (2012), I will use the term to refer to the vanishing procyclicality of productivity.

[2] Biddle (2014) notes that labour hoarding as a concept dates back to Okun (1962). By the 1980s, the concept was being regularly used as a standard textbook explanation for procyclical labour productivity (e.g., Dornbusch and Fischer (1981), Hamermesh and Rees (1984)). Ironically, from the mid-1980s labour productivity started losing its procyclicality.

[3] Real business cycle (RBC) models differ on the explanation of productivity procyclicality. They argue that business cycles are driven by procyclical technology shocks. In Section 2.2.3, I show evidence of negative response of labour inputs to positive technology shocks, which militates against the RBC paradigm.

case.

Having argued for the lowering employment adjustment cost as the key mechanism behind the productivity puzzle, I consider various structural changes in the labour market that can potentially explain a sudden drop in the cost of hiring and firing of workers in the mid-1980s, e.g., the decline of labour union power, the increased use of part-time and temporary workers, and the rise of online job search platforms. I identify rapid de-unionization since the early 1980s as the main reason for increased U.S. labour market flexibility. I show that states without right-to-work legislation and industries where labour unions were strong in the pre-1980 period witnessed a bigger loss in the political clout of unions in the era of de-regulation, and as a consequence experienced a greater decline in the procyclicality of productivity. Moreover, sectors that experienced larger de-unionization also had a bigger rise in the relative volatility of employment, corroborating further the role of unions in labour market frictions. I also consider international evidence from other OECD countries and show that not only does a de-unionization episode predict a fall in cyclical productivity correlations, but that this decline of unions is unlikely to be driven by labour market trends like skill-biased technological change. Countries like Canada and Sweden, which arguably experienced similar technological changes to the U.S., did not experience this de-unionization episode, while the pro-business stance of the Reagan and Thatcher administrations in the U.S. and the U.K. seems to have led to a sharp decline in union power in those countries. In this limited sense of exogeneity to labour market conditions, the politically driven sudden decline of union power can be thought of as a causal channel for explaining the productivity puzzle. While this paper shares with Gordon (2011) and Galí and van Rens (2020) the basic idea of falling hiring frictions as the explanation for the productivity puzzle, the identification of the decline of union power as the main channel for falling hiring frictions is one of the key contributions of this paper. In this sense, the paper can be thought of as an attempt to connect the role of an important labour market institution, namely unions, to its implications for determining business cycle dynamics.

To ascertain how much of the drop in cyclical productivity correlations can be quantitatively explained by the fall in labour adjustment cost induced by the de-unionization episode, I use a general equilibrium framework with endogenous movements in labour effort or utilization and costly hiring of workers by firms. Allowing the hiring cost to decrease by the same proportion as the decline in private-sector unionization rate in the U.S. can match almost all of the drop in cyclical productivity correlations and the rise in the relative volatility of employment. Recognizing that falling hiring frictions can be brought about by various forces other than de-unionization (e.g., in Spain, it was caused primarily by legislation allowing for greater hiring of temporary workers who are easier to hire and fire than their permanent counterpart), the model does not feature a micro-foundation of unions, rather a reduced form hiring cost which is allowed to change depending on the level of union density. However, apart from hiring cost, I also allow for the wage bargaining power of firms to increase due to de-unionization in the calibration and show that this channel is not quantitatively significant enough to explain the productivity puzzle.

The model not only quantifies the role of de-unionization for the productivity puzzle through reducing hiring cost and increasing the wage bargaining power of firms, but also assesses the roles played by other structural changes that occurred in the U.S. economy around the mid-1980s, viz., the reduction in the volatility of economic shocks in the Great Moderation, the increased importance of technology shock relative to demand shock, and a more accommodative monetary policy by the Federal Reserve. To be able to study these channels, the model features nominal rigidities in both goods prices and wages, and two shocks, viz., a technology shock to productivity, and a demand shock to monetary policy. The nominal rigidities help in generating impulse responses to technology and demand shocks that mimic the empirically observed ones in the SVAR analysis. Hence, in stark contrast to the modified RBC model in Galí and van Rens (2020), my model predicts a negative response of employment to positive technology shock and positive response of productivity to an expansionary demand shock. Moreover, in contrast to the argument in Barnichon (2010), I find that the increased importance of technology shock relative to demand shock in the post-1984 period cannot explain any significant part of the productivity puzzle. This is for two reasons: first, the property of technology shock inducing countercyclicality of productivity with labour input became muted after the 1980s, and second, technology shock always induced procyclicality of productivity with output and so its enhanced importance cannot explain the vanishing procyclicality of productivity with output.[4] Thus, a significant contribution of this paper is that in explaining the productivity puzzle not only can my model match the empirical change in the unconditional correlations of productivity but also those conditional on technology and demand shocks. Moreover, I find that neither a reduction of the shock volatilities during Great Moderation nor the more accommodative policy stance by the monetary authority had any significant impact on the productivity puzzle.

Beyond the model framework, I further consider other theoretical channels that have been proposed in the literature as explanations for the productivity puzzle and attempt to test them empirically. I do not find convincing evidence that more selective firing of low-productivity workers during recessions after the 1980s (see Berger (2016) and Ding and Hill (2017)), the rise of the service-sector either in terms of value-added or intermediate input use, increased productivity-enhancing inter-sectoral reallocation of employment during recessions (see Garin, Pries and Sims (2018)), or the increased use of intangible capital (see McGrattan and Prescott (2012)) significantly contributed to the vanishing procyclicality of productivity.

Two phenomena in recent decades have been related to the productivity puzzle in the literature: a sclerotic labour market and jobless recoveries. Decker et al. (2020) argue that decreased labour market turnover is most plausibly indicative of higher labour market frictions. While this might seem to go against the decline in hiring frictions stressed in this paper, Galí and van Rens (2020) argue that lower labour market turnover can induce a lower hiring cost in equilibrium. Moreover, the crucial

[4]Performing a comparative study of the change in the nature of technology and demand shocks on one hand, and the structural change in the labour market on the other, Van Zandweghe (2010) concludes that since the productivity correlations have changed conditional on both demand and supply shocks, it is more likely that change in labour market flexibility is the key factor behind the phenomenon.

argument in this paper is not that the absolute cost of employment adjustment has gone down but that the cost of extensive margin adjustment is lower relative to that of effort adjustment in the post-1980 era. While the model assumes costless effort adjustment and a decline in hiring cost, the main results will qualitatively go through with a rising cost of both effort and employment adjustments, provided employment adjustment costs rise less sharply. Nevertheless, the fall in job flow rates and jobless recoveries in the U.S. started from the 1990s, almost a decade after the productivity puzzle. So it is not clear whether the vanishing procyclicality of productivity since the mid-1980s should be explained by the same factors that led to jobless recoveries and reduced labour market turnover almost a decade later. Furthermore, even though jobless recoveries are consistent with the falling correlation between productivity and labour input, they are at odds with the falling correlation between output and productivity because such recoveries are characterized by a pick-up in both output and productivity but stagnation or a continuing drop in employment. Therefore, in this paper, I will focus exclusively on the structural changes in the economy that can explain the productivity puzzle, and not necessarily the phenomena of jobless recoveries and reduced labour market turnover.

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

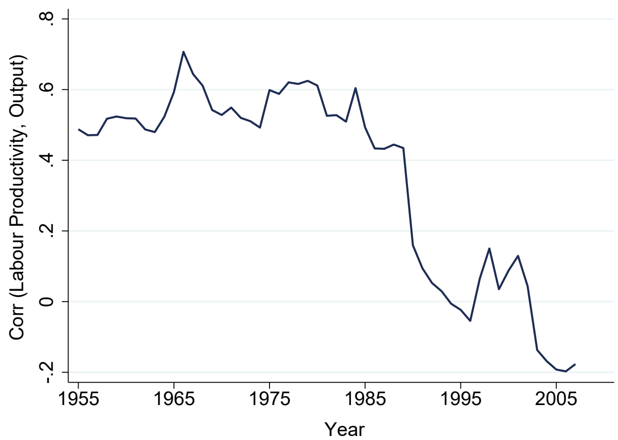
2 Explaining the Productivity Puzzle: Empirical Evidence

2.1 The Productivity Puzzle

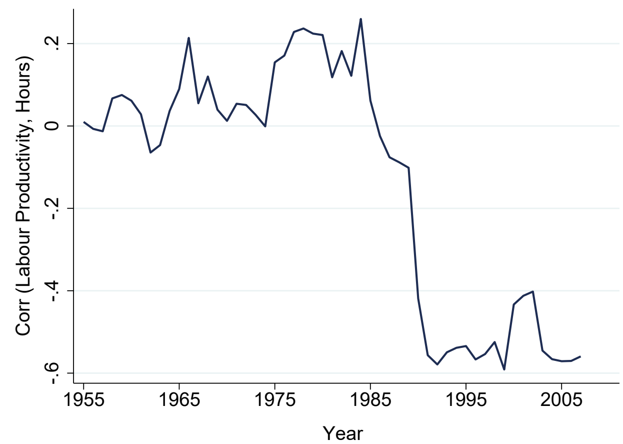
The *productivity puzzle* refers to the sudden vanishing of procyclicality of productivity around the mid-1980s in the U.S. The existing literature on this puzzle has typically used ALP, defined as output per hour worked, as the measure of productivity. In panels (a) and (b) of Figure 2.1, I corroborate that finding using quarterly data on output and total hours worked for the U.S. business sector from 1947 through 2017, sourced from the Labor Productivity and Costs (LPC) dataset of the Bureau of Labor Statistics (BLS). As an alternative measure of productivity, in panels (c) and (d), I use TFP (unadjusted for factor utilization), sourced from Fernald (2014), and find a remarkably similar pattern of a sudden drop in contemporaneous productivity correlations.[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 the sudden drop in the cyclical productivity correlations around the mid-1980s. While I have used the Baxter and King (1999) (henceforth BK)

[5]For a discussion on changes in non-contemporaneous correlations of productivity with output and labour input, see Brault and Khan (2020).

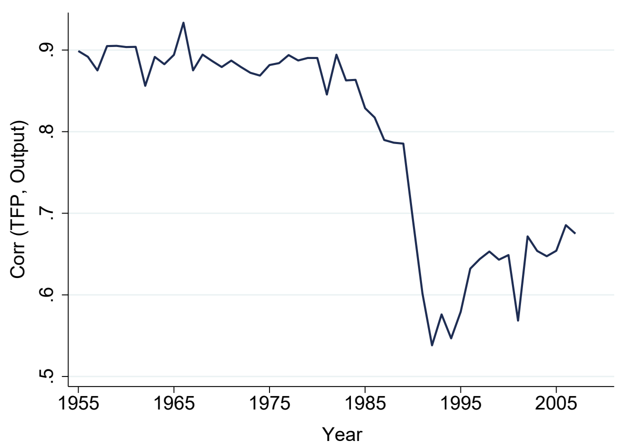
bandpass filter to extract the cyclical component of the time-series variables in Figure 2.1, the finding is robust to the choice of the de-trending method: quarterly and annual growth rates, and the Hodrick and Prescott (1997) (henceforth HP) filter. Findings are also robust to using quarterly data for the non-farm business sector from LPC, using annual KLEMS data by Jorgenson, Ho and Samuels (2012) for the aggregate U.S. economy, and using employment as the measure of labour input instead of total hours worked. Appendix A contains the complete set of robustness checks.



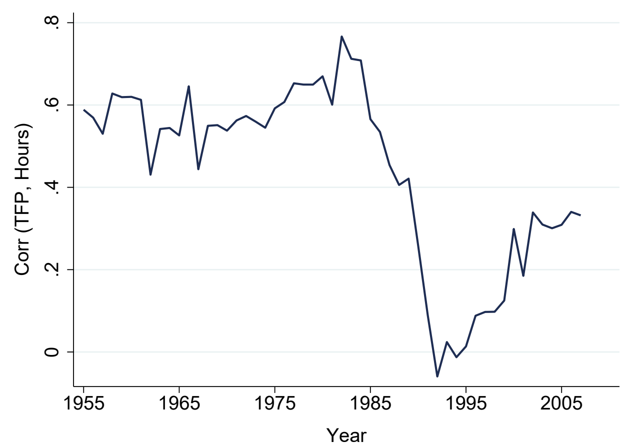
(a) Corr (Labour Productivity, Output)



(b) Corr (Labour Productivity, Hours)



(c) Corr (TFP, Output)

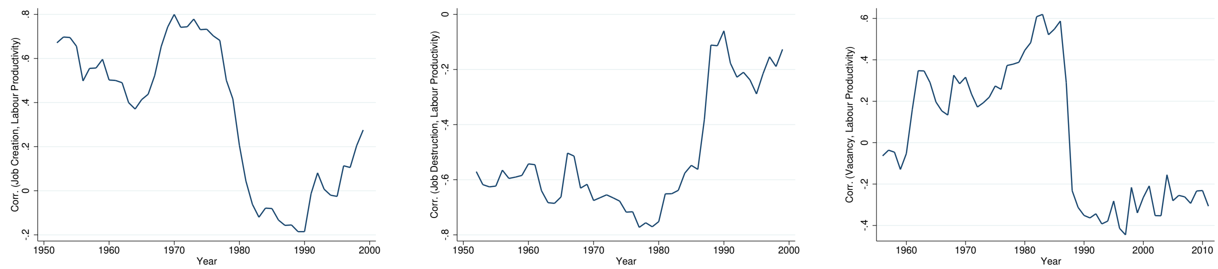


(d) Corr (TFP, Hours)

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. Relevant data for panels (c) and (d) are sourced from Fernald (2014), as modified by Ramey (2016). The measure of TFP is not adjusted for factor utilization. The Baxter and King (1999) bandpass filter between 6 and 32 quarters is used to filter all the variables. A centred rolling window of 15 years is used to calculate the correlations. Findings are robust to alternative choice of filters and window-sizes.

These changes in productivity correlations have implications for the co-movement of productivity with job flows over the business cycle. 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-destruction or separation rate more procyclical after the 1980s. Using different data sources on job flows, I corroborate these conjectures in Figure 2.2.



(a) Job Creation (b) Job Destruction (c) Help Wanted Index

Figure 2.2: Cyclical Correlation of Labour Productivity with Job Flows

Note: Panels (a) and (b) correspond to the U.S. manufacturing sector (data from Davis, Faberman and Haltiwanger (2006)), while panel (c) is for the entire U.S. economy (data from the *Job Openings and Labor Turnover Survey*). The Baxter and King (1999) bandpass filter between 6 and 32 quarters is used to filter all the variables. A centred rolling window of 10 years is used to calculate the correlations. Findings are robust to alternative choice of filters and window-sizes.

Having established that the productivity puzzle is not simply an artefact of a particular dataset, or a specific statistical filtering process, or the choice of the measure of productivity or labour input, I now consider possible explanations for the puzzle.

2.2 Explaining the Puzzle: A Drop in Employment Adjustment Cost

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

2.2.1 Vanishing Procyclicality 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 hours. For example, if labour is utilized at a higher rate (by increasing labour effort) during economic booms than during recessions then measured ALP will be more procyclical. This can be understood by simply studying a production function with effective labour input, $Y = AE^{\alpha_1}N^{\alpha_2}$, where Y is the value-added, E is the effort or utilization rate of each worker N, and A is the utilization-adjusted productivity component. ALP is defined as $\frac{Y}{N} = AE^{\alpha_1}N^{\alpha_2-1}$, which is non-increasing in N so long as $\alpha_2 \leq 1$. In an economic downturn, when firms want to reduce the effective labour input, $E^{\alpha_1}N^{\alpha_2}$, they face the option of either reducing the number of workers N, or decreasing the utilization rate E. When it is costly to adjust employment, firms mostly change effort. As an extreme example, when N is fixed over the business cycle due to costly adjustment, all change in ALP is explained by changes in effort. Thus, as firms increase E during booms and decrease it in recessions, ALP remains perfectly procyclical. As the cost of adjusting N falls, firms can now reduce N in recessions, thereby boosting ALP during economic downturns. Thus, a lower hiring and firing cost makes measured productivity less procyclical.

Table 2.1: Reduction in Procyclicality of Factor Utilization Rate

	Correlation with Output			**Correlation with Hours**		
Variable	Pre-1983	Post-1984	Change	Pre-1983	Post-1984	Change
TFP	0.87	0.70	- 0.17	0.35	0.10	- 0.25
Factor Utilization Rate	0.73	0.49	- 0.24	0.67	0.52	- 0.15
Utilization-Adjusted TFP	0.10	0.25	+0.15	-0.40	-0.32	+0.08

Note: Data on quarterly growth rates of all the variables for the U.S. business sector are sourced from Fernald (2014). Results are robust to using annual growth rates. Since Fernald (2014) only provides the growth rates of the three variables, robustness to other de-trending methods cannot be established.

Using hours per worker as a proxy that is proportional to unobserved changes in both labour effort and capital utilization, Basu, Fernald and Kimball (2001) generated a composite factor utilization rate series and a utilization-adjusted TFP series. Studying the cyclical property of those series in Table 2.1, one can conclude that the drop in cyclical correlations of measured productivity is driven by the factor utilization component of TFP, and not the 'true' productivity component. In Appendix Table A.4, I show that this drop in procyclicality of the utilization rate is robust to using the capacity utilization rate published by the Federal Reserve Board based on the Quarterly Survey of Plant Capacity by the Census Bureau. As discussed above, factor utilization can become less procyclical if factor adjustment along the extensive margin over the business cycle becomes more pervasive in comparison to changes in unobserved labour effort and work-week of capital.

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

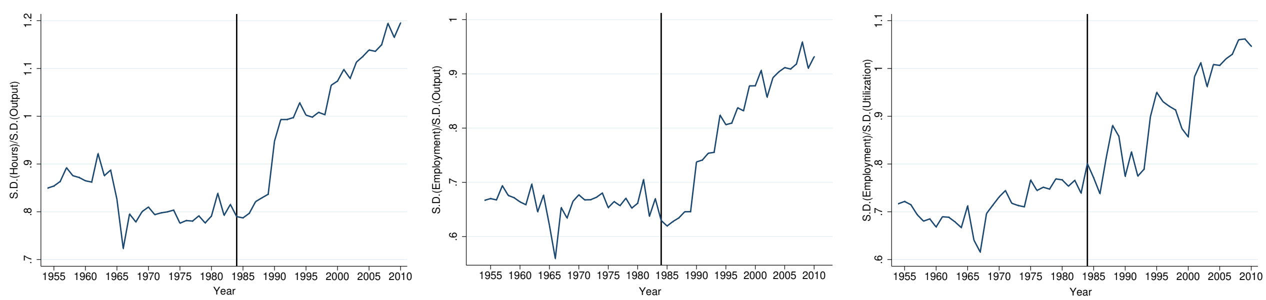
Table 2.2: Reduction in Variance of Factor Utilization Rate

Variable	Variances 1948-1983	Variances 1984-2017
TFP	17.55 (100%)	5.89 (100%)
Factor Utilization Rate	11.67 (66.5%)	1.64 (27.8%)
Utilization-Adjusted TFP	5.88 (33.5%)	4.25 (72.2%)

Note: Data on quarterly growth rates of all the variables for the U.S. business sector are sourced from Fernald (2014). Percentages in parentheses refer to the share of total variance of TFP that is explained by each component. The covariance term is equally split between the variances of the two components of TFP.

2.2.2 The Rising Relative Volatility of Employment

Falling employment adjustment cost should imply a rise in the volatility of employment relative to those of output and factor utilization. Figures 2.3a and 2.3b show the dramatic rise in the volatility of hours and employment relative to that of output exactly at the time of the sudden drop in the productivity correlations. Finally, Figure 2.3c shows how the relative importance of employment (the extensive margin of labour adjustment) vis-à-vis the intensive margin of factor utilization increased progressively from around the same time. This rise in the relative volatilities of measured labour inputs happened immediately after the onset of the so-called Great Moderation, when the absolute volatilities of output and labour input fell precipitously in the late 1970s. As is evident from Appendix Table A.2, even though the volatilities of output, hours and employment declined unanimously, the magnitude of reduction in volatility is larger for output than for the labour inputs. This leads to the eventual increase in the volatility of labour input relative to that of output.



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

Figure 2.3: Relative Volatility of Hours & Employment over the Business Cycle (1954-2010)
Note: Data for hours, employment and output is sourced from the BLS-LPC quarterly dataset for the U.S. business sector. Factor utilization data (in quarterly growth rates) is taken from Fernald (2014). The Christiano and Fitzgerald (2003) bandpass filter between 6 and 32 quarters have been used to extract the cyclical component of the variables in panels (a) and (b) since the BK filter distorts the amplitude of the extracted cycle, while the annualized quarterly growth rate has been used in panel (c) since data on factor utilization is only available in growth rates. A centred rolling window of 15 years is used to calculate the second moments. Findings are robust to alternative choice of filters and window-sizes.

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

2.2.3 Changes in Response to Technology and Demand Shocks

Structural changes in the labour market that make hiring and firing of workers easier for firms should have implications for how the economy responds to different types of shock. 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 that labour productivity will not rise (because of no increase in worker effort) in response to a positive demand shock when employment adjustment costs were low in the post-1980s. To ascertain whether this is indeed the case, I study the changes in the impulse responses of labour input (per capita total hours worked) and productivity to technology and demand shocks between 1950 and 2017. Following Galí and Gambetti (2009), I run a time-varying structural vector auto-regression (SVAR) with two variables: ALP growth and per capita hours. The technology shock is identified as the only innovation that influences productivity growth in the long run (see Galí (1999)), while the remaining disturbance is named the demand shock.[6]

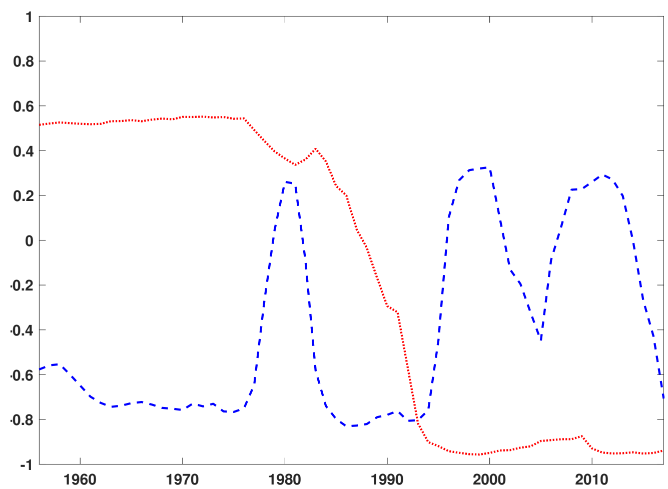


Figure 2.4: Conditional Correlations of Productivity with Hours

Note: Time-varying correlations of per capita hours with labour productivity, conditional on technology shock (blue dashed line) and demand shock (red dotted line). This is a replication of a result in Galí and Gambetti (2009) with updated data from 2005 to 2017.

The starkest finding in Figure 2.4 is the sudden and massive reduction in the correlation between per capita hours and productivity conditional on a demand shock around the mid-1980s, shown by the red dotted line. This corroborates the narrative of falling labour market frictions in the post-

[6]In Appendix B, I discuss the rationale behind the choice of this SVAR specification, along with the resulting time-varying impulse responses, and robustness to using TFP instead of ALP as the productivity measure. A local projection analysis using utilization-adjusted TFP growth as the technology shock, that bypasses this identifying assumption, is also shown to generate similar impulse responses for per capita hours worked.

1980 period. Additionally, there are two important features of the correlation between hours worked and ALP conditional on a technology shock, shown by the blue dashed line in Figure 2.4. First, the negative correlation between per capita hours and ALP conditional on a positive technology shock for most years before the mid-1980s reveals that hours worked decreased in response to a positive technology shock. This implies that the procyclicality of productivity with labour input in the pre-1980 period is not driven by technology shocks, thereby making the real business cycle theory about the procyclicality of productivity invalid. Second, conditional on a technology shock, the correlation between hours and productivity has increased for most years since the 1990s, probably due to more accommodative monetary policy by the Federal Reserve in the Volcker era. This muted negative response of hours to a positive technology shock increases the productivity correlation with labour input. This acts as a counterforce to the vanishing procyclicality of productivity.

The reduction in productivity correlation conditional on a demand shock shows that it is not the case of a changing composition of technology versus demand shocks to the U.S. economy that have induced the sudden fall in unconditional productivity correlation (as is claimed in Barnichon (2010)). Rather, there must have been deeper structural changes like increased labour market flexibility that made the economy respond differently to the same shocks in the post-1980 period.

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

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

I consider various possible causes for a decline in the employment adjustment cost, viz., the rise of online job search platforms, the increased use of temporary and part-time workers, and de-unionization. I show in Appendix C that while the first two channels can potentially explain falling productivity correlations in other countries (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), they do not offer a satisfactory explanation for either the timing or suddenness of the productivity puzzle for the U.S. However, in Figure 2.5, I show that the 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.

In Figure 2.6 we see that union membership among working individuals, both in terms of rates and absolute numbers, was rising in the U.S. until the 1950s, after which it remained roughly flat for three decades (with falling rates for the private industries and increasing rates for the public sector in the 1970s), and started falling sharply from the early 1980s with a decline of roughly 50% in aggregate

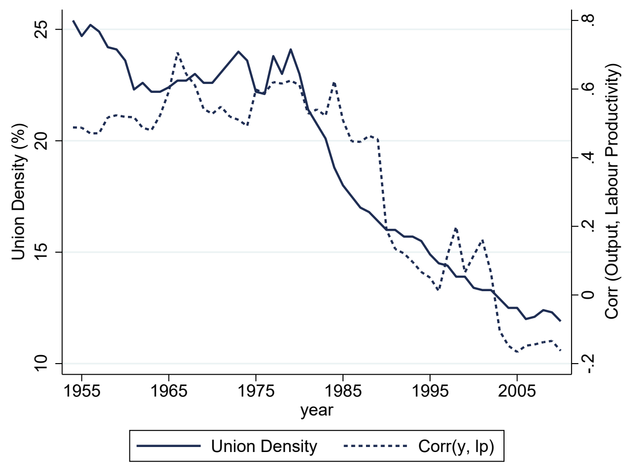


Figure 2.5: De-unionization & Productivity Puzzle

and 67% in the private sector by 2010.[7] It is interesting that when union density was rising before World War II, mirroring what happened in the 1980s, productivity had turned more procyclical. Using HP-filtered annual data for the non-farm business sector, I find that cyclical correlation between output per worker and output (employment) started low at 0.42 (-0.14) between 1939 and 1946, rising to 0.77 (0.20) between 1947 and 1983, and then falling again to 0.57 (0.01) between 1984 and 2019. This is further corroboration of the role of unions in influencing cyclical productivity correlations, even in the long run.

Farber and Western (2002) argue that the stark reversal of the trend 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,[8] and the much-publicized appointment of the Reagan Labor Board in 1983. A change in the political climate implies that changes in union density may be an underestimate of the change in the real bargaining power of unions. While it is difficult to measure the power of unions directly, one good proxy is the number of work stoppages, which are usually organized by unions. From Figure 2.7, one can see that large-scale work stoppages dropped by almost 90% of their pre-1980 level quite suddenly within a couple of years. Thus, although the decline in union membership from the early 1980s was a somewhat gradual process, which might seem inconsistent as an explanation for the strikingly rapid

[7] Consistent data on union density is available separately for the private-sector only from 1973 onwards (see Hirsch and Macpherson (2003)). Although unionization rate started falling from the early 1970s in the private-sector, the de-unionization 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. Based on a different data-source, 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.

[8] 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.

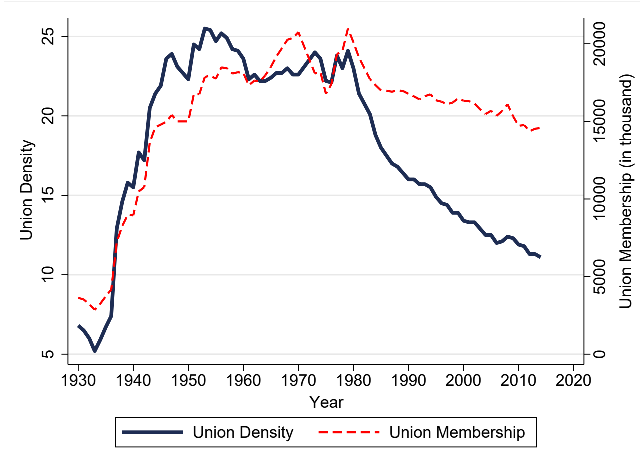


Figure 2.6: Size & Density of Labour Union Membership in the U.S. (1930-2014)
Note: Figures represent the number and percentage of non-agricultural wage and salary employees who are union members. Data before 1977 is sourced from Historical Tables published by the BLS. Data between 1977 and 1981 comes from May earnings files, and from 1983 onwards it comes from the Outgoing Rotation Group (ORG) earnings files of the *Current Population Survey* (CPS), collected by Hirsch and Macpherson (2003). Union coverage rates are slightly different from union membership rates but follow a similar time-trend.

decline in the productivity correlations, union power seems to have declined more promptly.

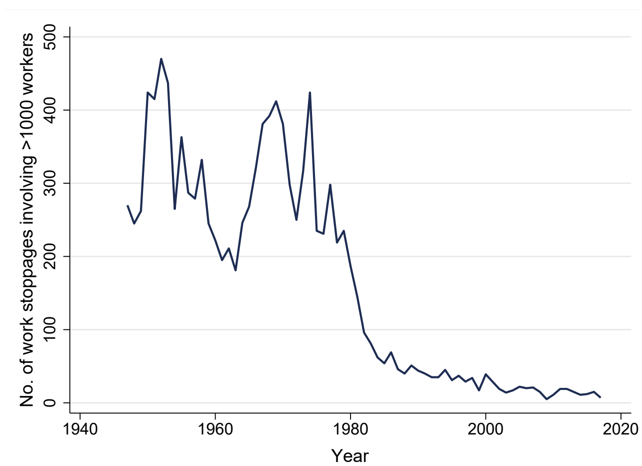


Figure 2.7: Number of Work Stoppages involving 1,000 or more workers in the U.S. (1947-2017)
Note: Data is sourced from the Economic News Release of the Bureau of Labor Statistics (BLS).

The era of deregulation that began in the U.S. in the early 1980s had its parallel in other parts of the world. The U.K., which underwent a similar episode 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. In Figure 2.8, I show that in most of the developed world, de-unionization is strongly predictive of the loss in productivity procyclicality. This evidence is consistent in spirit with Gnocchi and Pappa (2009), who find that union coverage is the labour market rigidity that most significantly affects business cycle statistics in OECD countries. Moreover, the fact that de-unionization did not occur in some advanced economies of the world (like Canada, Sweden and Finland) makes it unlikely that the sudden trend reversal in union density in the U.S. was mainly driven by underlying labour market changes like skill-biased technological change (SBTC),[9] which arguably affected all developed economies. Furthermore, insofar as one believes that SBTC in the 1980s was driven by IT capital use (due to high capital-skill complementarity as highlighted in Krusell et al. (2000)), one should find a significant correlation across industries between the rising share of IT capital and falling productivity correlations. This is however not the case, as pointed out by Wang (2014). Therefore, while it could be the case that relatively slow-moving 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 precipitated by political factors that are exogenous to labour market conditions. It is in this sense of exogeneity that the impact of de-unionization on the falling procyclicality of productivity can be thought of as a *causal* channel.

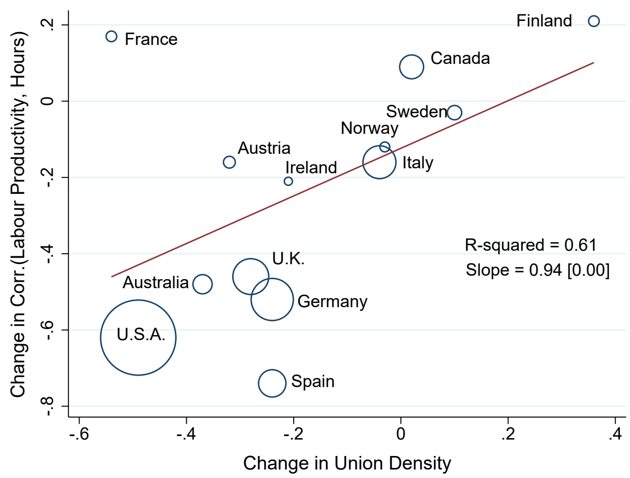


Figure 2.8: International Evidence for De-unionization

Note: All changes are between the post and pre-1984 periods. Labour productivity is defined as real GDP per hour worked. Quarterly data on output and hours between 1960 and 2010 for all countries (except Spain) are taken from*OECD Economic Outlook Database*, collected by Ohanian and Raffo (2012). Annual data for Spain between 1950 and 2017 is sourced from the *Conference Board Total Economy Database*. De-trending of variables has been done using the HP-filter. Union density data are sourced from *OECD Annual Trade Union Density Dataset*. 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.

De-unionization in the U.S. was a primarily within-industry and within-state phenomenon. A within-between decomposition reveals that about 88% and 91% of the fall in union density happened *within* industries and states respectively, and not through employment shifts towards less unionized

[9] Acemoglu, Aghion and Violante (2001) and Dinlersoz and Greenwood (2016) argue that SBTC can explain de-unionization in the U.S., while Açikgöz and Kaymak (2014) show that roughly 40% of the drop in unionization rates in the U.S. can be explained by the rise in the skill premium in wages. Foll and Hartmann (2019) argues that routine task-biased technical change is the driving force not only behind job market polarization but also de-unionization.

sectors and regions.[10] 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 cross-sectional regression:

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

where alp_i and h_i are the cyclical components of average labour productivity and total hours worked in industry or state i. In order to avoid the results being driven by small industries or states, I weight each observation with the average employment level in the corresponding industry or state.

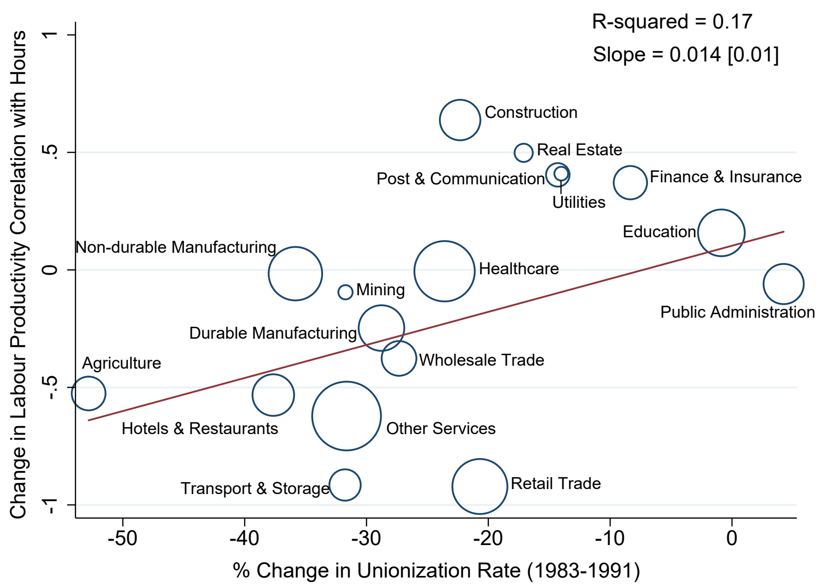


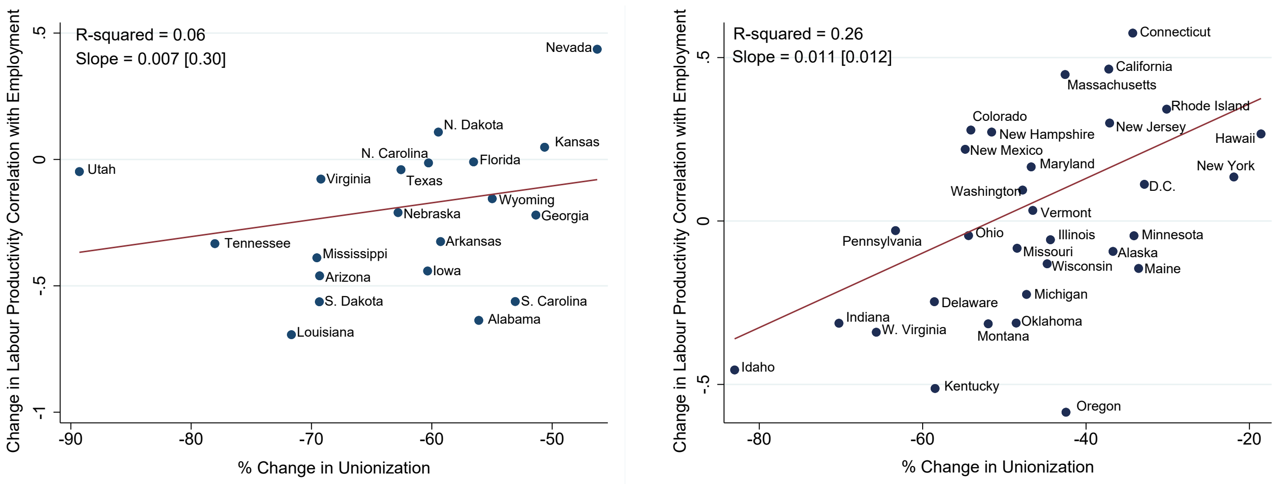
Figure 2.9: Cross-Industry Evidence for De-unionization

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

Figure 2.9 shows a significant positive relationship between the degree of de-unionization and the drop in productivity correlations across 17 U.S. industries. For the state-level regression, there is an additional concern that in recent years many U.S. states have adopted Right-to-Work (RTW) legislation promoting their "pro-business" outlook, thereby rendering the role of labour unions quite limited there. A decline in union density in those states that had RTW laws before 1984 should

[10]Total change in union density, $\Delta u =$ Within-i change, $\sum_{i=1}^{17} \bar{e}_i \Delta u_i$ + Between-i change, $\sum_{i=1}^{17} \bar{u}_i \Delta e_i$, where $\bar{e}_i$ is the average employment share and $\bar{u}_i$ is the average union density in industry or state i.

therefore barely matter for explaining the drop in productivity correlations. In Figure 2.10, 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).



(a) Right-to-Work States

(b) Non Right-to-Work States

Figure 2.10: Cross-State Evidence for De-unionization

Note: Categorization of states into *Right-to-Work* and *Non Right-to-Work* has been done based on the status in 1984. Data on state-level unionization rates comes from the CPS, collected by Hirsch and Macpherson (2003). State-level data on real non-farm gross domestic product and total employment between 1969 and 2010 is sourced from the BEA. Since hours worked data is not available at the state level, employment is used as the measure of labour input and labour productivity is defined as the state real non-farm gross domestic product per worker. I use annual growth rate as the filter because the preferred BK bandpass filter leads to 12 years of missing observations and leaves only 3 years of data before 1984. All changes in variables are calculated as the difference between the pre and post-1984 averages. Although observation for each state is weighted by its average employment in the regression, to improve readability I have not shown the weights here through bubbles, rather made it explicit in Appendix Figure E.1. The p-value of the slope coefficient using robust standard error is reported in parentheses.

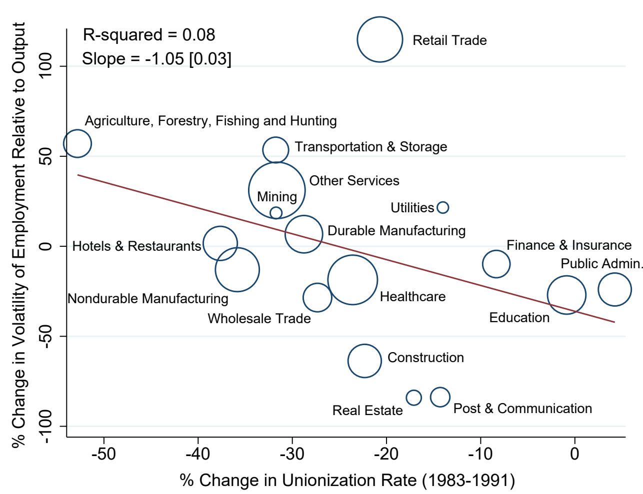


Figure 2.11: Relative Volatility of Employment and De-unionization

Note: See notes to Figure 2.9 for details regarding data sources.

One alternative identification strategy to the one considered above is to perform a difference-in-difference estimation à la Card (1992). In that strategy, one assumes that the intensity of the de-unionization event is 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 D for details).

The final piece of cross-sectional evidence in favour of de-unionization for explaining the falling cost of employment adjustment is a statistically significant negative relation between the rise in the relative volatility of employment and the drop in union density across U.S. industries (see Figure 2.11).

Summary of empirical findings and the need for a model — I have shown so far that the sudden vanishing of the procyclicality of productivity can be explained by a drop in employment adjustment costs that led to firms relying less on labour hoarding. Using cross-sectional evidence from OECD countries, as well as across states and industries within the U.S., it was argued that de-unionization is the leading reason for enhanced labour market flexibility in the U.S.

The model in the next section tries to quantify how much of the observed changes in cyclical productivity fluctuations can be explained by the falling employment adjustment cost channel. In addition, it makes explicit the relative quantitative importance of various other contemporaneous structural changes in explaining the productivity puzzle, e.g., a more accommodative monetary policy in the Volcker-era and the reduced shock volatility during the Great Moderation. While doing so, the model qualitatively matches the empirically observed impulse responses of labour input and productivity to technology and demand shocks, a property missing from previous models in the literature. Being able to generate correct signs of impulse responses is crucial to ascertain the changing role of shocks in explaining the productivity puzzle.

3 Model

I consider a New Keynesian model with two exogenous shocks — a technology shock to firm productivity, and a monetary policy shock to the nominal interest rate. I choose this set-up for a variety of reasons: first, the nominal rigidities in a New Keynesian framework allow me to generate the empirically observed negative response of labour input to a positive technology shock; second, having a monetary policy in the model allows me to quantify the role of more accommodative monetary policy in the Volcker-era for explaining the productivity puzzle; third, the two-shock set-up directly mimics the SVAR analysis in the empirical section; and fourth, the choice of the demand shock as the monetary shock, as opposed to a preference shock, allows me to measure the volatility of the shock directly in the data. I will deviate from the textbook model (see Galí (2008)) in two directions: first, I explicitly consider both extensive and intensive margins of labour input adjustment (namely, employment and effort); and second, I consider the presence of a convex cost of employment adjustment for firms. Notably, 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 rising use of temporary workers and online job search platforms, which are relevant for different countries at different time-periods. Nevertheless, in calibrating the model parameters for the U.S. economy, I allow the hiring cost to fall by the same proportion as the extent of de-unionization because, as was argued above, the decline of union power is the most important channel for falling employment adjustment costs in the U.S. Crucially, the absence of adjustment costs along the intensive margin of effort variation will lead firms to depend more on effort adjustment when hiring costs are high. This drives the main result of vanishing procyclicality of effort and labour productivity in the post-1984 era when hiring costs decreased significantly. In what follows, I lay out the model structure, with the complete set of log-linearized equations collected in Appendix G.

3.1 Households

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

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

subject to the per-period budget constraint,

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

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

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

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

$$C_{it} = \left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} C_t \tag{3.1}$$

The intertemporal optimality condition is given by

$$Q_t = \mathbb{E}_t \left(\frac{P_t}{P_{t+1}} \Lambda_{t,t+1}\right) \tag{3.2}$$

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

3.2 Firms

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

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

$$P_{it} = \left(\frac{\varepsilon}{\varepsilon - 1}\right) P_t^I \tag{3.3}$$

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

$$p_t = \theta_p p_{t-1} + (1 - \theta_p) p_t^* \tag{3.4}$$

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

$$p_t^* = \mu^p + (1 - \beta\theta_p) \sum_{k=0}^{\infty} (\beta\theta_p)^k \, \mathbb{E}_t \left(p_{t+k}^I\right) \tag{3.5}$$

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

$$\pi_t^p = \beta \mathbb{E}_t \left(\pi_{t+1}^p\right) - \lambda_p \hat{\mu}_t^p \tag{3.6}$$

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

Intermediate Goods — Each perfectly competitive intermediate goods firm $j \in [0,1]$ faces the production function $Y_{jt}^I = A_t \left(E_{jt}^{\psi} N_{jt}\right)^{(1-\alpha)}$, where A_t is the technology term common across all firms, the parameter $\psi \in (0,1)$ measures the additional returns to effort over employment, and $\alpha \in (0,1)$ denotes non-labour income share in the economy.[11] In the calibration in Section 4.1, the parameters ψ and α are chosen so as to satisfy non-increasing returns to scale: $(1-\alpha)(1+\psi) \leq 1$. The productivity term A_t has the following exogenous stochastic process: $a_t \equiv \ln(A_t) = \rho_a a_{t-1} + \varepsilon_t^a$, where ε_t^a is a white noise process with variance $\sigma_{\varepsilon^a}^2 > 0$. Since the production function explicitly includes the factor utilization term, namely, effort E_{jt}, the productivity term A_t should be interpreted as the utilization-adjusted TFP.

Labour Market — Workers get separated from their jobs at intermediate goods firms at the exogenous gross rate of $\delta \in (0,1)$, but every period t firm j hires back new workers H_{jt} $\forall j$, subject to a per-worker adjustment cost, $G_t = \Gamma H_t^{\gamma}$, where $H_t \equiv \int_0^1 H_{jt} dj$ denotes aggregate level of hiring in the economy. The assumption of a hiring cost as opposed to a firing cost is best motivated in Heckman et al. (2000): *"...in the face of a positive shock firms may want to hire additional workers, but they will take into account that some workers may have to be fired in the future if demand turns down. This prospective cost acts as a hiring cost..."*[12] Moreover, more powerful unions can cause this hiring cost to

[11] 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 F, 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 has so far been impossible to distinguish between capital utilization and worker 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 not be possible to separately identify time-variation in capital and employment adjustment costs.

[12] See Cooper, Haltiwanger and Willis (2007) for analysis involving hiring and firing costs with non-convexities in vacancy posting in a search framework with both employment and hours per worker variation.

rise for firms. This link between union density and hiring cost will be crucial later for the calibration of the model. Nonetheless, the presence of the job separation rate and the hiring by the firm implies that employment at firm j has the following law of motion

$$N_{jt} = (1 - \delta) N_{jt-1} + H_{jt} \tag{3.7}$$

Because of the presence of labour market frictions in the form of a hiring cost, wages and employment may differ across firms, since they cannot be instantaneously arbitraged out by 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.[13] This assumption ensures that in a symmetric equilibrium all workers receive the same wage equal to the ex-post average wage. Hence, in what follows, I drop the subscript j.

Faced with the common hiring cost function, G_t and given the nominal wage W_t, a firm's optimal hiring policy is given by the condition,

$$MRPN_t = \frac{W_t}{P_t} + G_t - (1 - \delta)\mathbb{E}_t \left(\Lambda_{t,t+1} G_{t+1}\right) \tag{3.8}$$

where $MRPN_t = (1 - \alpha)(1 - \Psi_F) \frac{P_t^I}{P_t} \frac{Y_t^I}{N_t}$ is the marginal revenue product of employment expressed in terms of final goods. The non-zero term $\Psi_F \equiv \frac{\alpha\psi}{1+\phi-(1-\alpha)\psi}$ arises due to the endogenous response of effort to changes in employment. This condition implies that each period the firm hires workers up to the point where the marginal revenue from an additional employment equals the cost of that marginal worker, where the cost involves not only the wage and the hiring cost in the current period, but also the discounted future savings from having to hire $(1 - \delta)$ fewer workers in the following period. Solving equation (3.8) forward, one has the following expression for the average hiring cost,

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

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

$$MRPN_t = \frac{W_t}{P_t} + B_t \tag{3.10}$$

Given that the average frequency of wage changes is more than one year in the data, I assume nominal wages are negotiated every period with probability $(1 - \theta_w)$ through a Nash bargaining process between the intermediate goods firms and the households to split the total surplus gener-

[13] 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.

ated from an established employment relation. Thus, similar to goods prices, the law of motion for nominal wage, W_t becomes a weighted average of the optimally chosen wage, W_t^* and the last period's wage, W_{t-1}: $w_t \equiv \int_0^1 w_{jt} dj = \theta_w w_{t-1} + (1-\theta_w) w_t^*$ in log-terms.

The surplus at time $t+k$ accruing to a firm which had last set its wage optimally in period t, and the household members who work at the firm are given by the following two equations respectively,

$$\begin{aligned} S^F_{t+k|t} &= MRPN_{t+k|t} - \frac{W_t^*}{P_{t+k}} \\ &+ (1-\delta)\,\mathbb{E}_{t+k}\left\{\Lambda_{t+k,t+k+1}\left(\theta_w S^F_{t+k+1|t} + (1-\theta_w)\,S^F_{t+k+1|t+k+1}\right)\right\} \qquad (3.11) \\ S^H_{t+k|t} &= \frac{W_t^*}{P_{t+k}} - MRS_{t+k} \\ &+ (1-\delta)\,\mathbb{E}_{t+k}\left\{\Lambda_{t+k,t+k+1}\left(\theta_w S^H_{t+k+1|t} + (1-\theta_w)\,S^H_{t+k+1|t+k+1}\right)\right\} \qquad (3.12) \end{aligned}$$

for $k = 0, 1, 2, ...$, where $MRS_t = \frac{\chi C_t}{1+\zeta} + \Psi_H \frac{P_t^I}{P_t}\frac{Y_t^I}{N_t}$ is the household's marginal rate of substitution between consumption and employment, or equivalently the marginal disutility of employment expressed in terms of the final goods bundle. The non-zero term $\Psi_H \equiv \frac{\psi}{1+\phi}\left(1 - \frac{(1+\phi)W_t N_t}{(1+\phi-\psi)P_t C_t}\right)$ arises due to the endogenous response of effort to changes in employment. Profit maximization by firms implies that the firm surplus, $S^F_{t+k|t}$ equals the per worker hiring cost, G_{t+k} for all t and k. The average hiring cost can thus be interpreted as what the firm potentially saves from maintaining an existing employment relation.

Denoting the relative bargaining power of firms vis-à-vis workers by the parameter $\xi \in (0,1)$, the Nash bargaining set-up solves the following problem

$$\max_{\{W_t^*\}} \left(S^F_{t|t}\right)^{\xi}\left(S^H_{t|t}\right)^{1-\xi}$$

subject to equations (3.11) and (3.12). The solution to the above bargaining problem implies a constant share rule, $\xi S^H_{t|t} = (1-\xi)\,S^F_{t|t}$, which translates to the equilibrium wage condition,

$$\mathbb{E}_t\left[\sum_{k=0}^{\infty}\{(1-\delta)\,\theta_w\}^k\,\Lambda_{t,t+k}\left(\frac{W_t^*}{P_{t+k}} - \Omega^{target}_{t+k|t}\right)\right] = 0 \qquad (3.13)$$

where $\Omega^{target}_{t+k|t} \equiv \xi MRS_{t+k} + (1-\xi)\,MRPN_{t+k|t}$ is the Nash-bargained wage under a flexible wage environment.

3.3 Monetary Policy

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

$$i_t = \rho i_{t-1} + (1-\rho)\left(\phi_\pi \pi_t^p + \phi_y \hat{y}_t\right) + \phi_{\Delta y}\Delta\hat{y}_t + \nu_t \qquad (3.14)$$

where $i_t \equiv -\ln Q_t$ is the nominal yield on a one-period riskless bond, ρ is the persistence in monetary policy, $\hat{y}_t$ is the logarithm of the period t output gap in the economy, and ν_t is the exogenous policy shifter. The monetary policy shock ν_t is assumed to follow an AR(1) process: $\nu_t = \rho_\nu \nu_{t-1} + \varepsilon_t^\nu$, where the persistence parameter $|\rho_\nu| < 1$ and ε_t^ν is a white noise process with variance $\sigma_\nu^2 > 0$. The degree to which the Central Bank accommodates exogenous shifts in productivity partly determines the coefficient of the output gap in the Taylor rule. In particular, the smaller the parameter ϕ_y, the more accommodating is the monetary policy. Since I have already shown empirically that the response of hours and employment turned less countercyclical or sometimes even procyclical after 1984, one can expect to see the parameter ϕ_y turning smaller in magnitude in the later years. It should be noted that a countercyclical response of employment to a technology shock is contingent on the monetary policy being not too accommodative.

3.4 Equilibrium Conditions

I assume that hiring costs take the form of a bundle of final goods given by the same aggregation as the one defining the consumption index. This implies that the demand for each final good is given by $Y_{it} = \left(\frac{P_{it}}{P_t}\right)^{-\varepsilon}(C_t + G_t H_t)$. The goods market clearing condition is thus given by

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

In the neighbourhood of a zero-inflation steady state, the price dispersion caused by price and wage rigidities is negligible, which implies that intermediate input and final goods are equal in aggregate, $X_t \simeq Y_t$, and that the aggregate production function is given by

$$Y_t \simeq A_t \left(E_t^\psi N_t\right)^{(1-\alpha)} \tag{3.16}$$

4 Quantitative Analysis

I calibrate the parameters of the model to reasonable values often estimated in the literature and then check whether structural changes in some of them between the pre and post-1984 periods can generate the empirically observed changes in the business cycle moments in question.

4.1 Calibration

For ease of exposition, I discuss the calibration of the entire set of parameters in four groups: (i) parameters affected by de-unionization, namely, the steady-state share of hiring cost in GDP, Θ and the wage bargaining power, ξ; (ii) the accommodative stance of monetary policy, ϕ_y, which changed during the Volcker-era, and had an impact on the economy's response to technology shocks; (iii) parameters pertaining to the volatility of the exogenous shocks to technology and monetary policy, namely, σ_a and σ_ν, which decreased during the Great Moderation; and (iv) other parameters that I will consider to have remained stationary over the period under study.

Structural Changes due to De-unionization — Denoting by Θ the steady-state share of total hiring cost in real output, i.e., $\Theta \equiv \left(\bar{G}.\bar{H}/\bar{Y}\right)$, a fall in hiring cost can be captured by a decrease in Θ in the post-1984 period. I consider a fall in the share of the hiring cost in GDP from 3% in the pre-1983 period to 1% in the post-1984 era. These magnitudes are in line with the estimates of the hiring cost share by Silva and Toledo (2009) and used for calibration in Hagedorn and Manovskii (2008). They estimate hiring cost to be roughly 4.5% of the average quarterly wage. Assuming the average wage to be 67% of real output, given by the labour share in total compensation, the hiring cost as a share of GDP is calibrated to be 3% in the pre-1984 period. Now, the union membership rate in private non-farm U.S. industries was about 21% in 1979, after which time it started falling sharply, and reached 1/3 of that value at roughly 7% by 2009. I, therefore, calibrate the hiring cost share in GDP in the post-1984 era as 1/3 of its pre-1984 value of 3%.[14]

Table 4.1: Differences in Calibration between Pre- and Post-1984

Parameter	Meaning	Pre-1984	Post-1984
De-unionization			
Θ	Share of hiring cost in GDP	3%	1%
ξ	Wage Bargaining Power of Firms	0.50	0.84
Monetary Policy			
ϕ_y	Response to output gap	0.17	0.08
Shocks			
σ_a	Technology shock volatility	1.00	0.70
σ_ν	Monetary shock volatility	0.53	0.27

De-unionization not only affects the hiring cost of workers but also increases the wage bargaining power of firms. Assuming equal bargaining power, i.e., $\xi = 0.50$, for calibration purposes, is the standard in the literature. Felix and Hines Jr. (2009) find that workers in a fully unionized firm capture roughly 54% of the benefits of lower state corporate income tax rates in the U.S., which roughly indicates an equal bargaining power between workers and firms. Starting from an equal bargaining power between workers and firms in the pre-1983 period, I allow the parameter to increase by 67% in the post-1984 period to 0.84, mirroring the fall in union density in the private nonfarm business

[14] Galí and van Rens (2020) also consider a fall in the share of hiring cost from 3% to 1% of GDP, but their calibration choice is motivated by a 67% fall in the gross job separation rate, $s/(1-f)$, where s is the exit rate and f is the job-finding rate. However, as shown in Appendix C, data on quarterly job flows from Shimer (2012) show that gross job separation rate fell by only about 12% (from 6.7% to 5.9%) in the post-1984 era with the decline starting after 1990. Also, reduction in the job separation rate appears to be an unlikely explanation for the fall in hiring costs when international evidence is taken into account.

sector in the U.S.

Monetary Policy Change — Smets and Wouters (2007) estimate the Taylor-rule parameters separately for two periods: 1966 through 1979, and 1984 through 2004, and find that ϕ_y decreased from 0.17 to 0.08 between the two periods, with no other significant changes in other parameters. This decline in ϕ_y captures a more accommodative monetary policy and a relatively larger weight attached to inflation by the Federal Reserve under Paul Volcker. This change in the stance of the monetary policy counteracts the fall in productivity correlation with the labour input through the reduced negative response of hours on the impact of a positive technology shock in the post-1984 period.[15]

Shock Volatility Changes during the Great Moderation — Barnichon (2010) finds the standard deviations of technology and demand shocks to have declined by 30% and 50% respectively in the post-1984 period using a SVAR analysis. I corroborate these findings from external evidence by studying the change in the volatility of utilization-adjusted TFP from Fernald (2014) (see Table 2.2) and the volatilities of the monetary shocks estimated by Romer and Romer (2004) and Sims and Zha (2006) (see Appendix H). This asymmetric reduction in volatilities of the technology and demand shocks makes technology shocks relatively more important in the post-1984 era. While technology shocks do induce countercyclicality of productivity with labour input (albeit in a muted fashion after the 1990s), they always induce procyclicality of productivity with output. Hence, contrary to the claim in Barnichon (2010), the enhanced importance of technology shocks is an unlikely candidate for explaining the productivity puzzle.

Stationary Parameters — The fourth set of parameters corresponds to those which have arguably not changed significantly between the pre and post-1984 periods. The complete list of these parameters and their calibrated values are presented in Table 4.2. While most of the parameters are calibrated to some well-established estimates in the literature, few (marked by *) are somewhat arbitrarily chosen and robustness of the model's quantitative performance to their alternative values is shown in Appendix H. I discuss these parameters below.

The total hiring cost, $G_t.H_t$ is assumed to be convex in aggregate hiring, following the finding in King and Thomas (2006).[16] In the baseline calibration of the model, the average hiring cost function is taken to be quadratic, that is, $\gamma = 1$. However, there is no agreement in the literature about the degree of convexity of the function. Mortensen and Nagypál (2007) find that in the presence of search frictions with linear vacancy posting costs, the matching function has an unemployment elasticity of 0.6. Interpreting employment adjustment costs as search frictions, a natural calibration for γ in the current model is 0.6. On the other hand, Merz and Yashiv (2007) directly estimate the convexity of the average employment adjustment cost and report a value of 2.4. In Appendix H, I show the robustness

[15] Clarida, Galí and Gertler (2000) find an increase in ϕ_π instead of a decrease in ϕ_y. In Appendix Table H.5, I show the robustness of the main findings of this paper to an increase in ϕ_π from 1.01 to 2.20 between the pre and post-1984 periods. I do not allow ϕ_π to be lower than 1.0 to avoid indeterminacy of multiple equilibria.

[16] 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.

of the quantitative model predictions for different values of γ in this range.

Table 4.2: Calibration of Time-Invariant Parameters

Parameter	Value	Calibration
β	0.99	Real risk-free annual interest rate $\simeq$ 3%
ε	10.0	Mark-up over marginal cost $\simeq$ 11%
α	0.33	Share of non-labour input in total compensation
θ_p	0.75	*Calvo nominal rigidity; Galí (2011)
θ_w	0.75	*Nominal wage rigidity; Galí (2011)
δ	0.10	Quarterly gross job separation rate; Shimer (2012)
ϕ_π	1.70	*Taylor rule response to inflation; Smets and Wouters (2007)
$\phi_{\Delta y}$	0.20	Taylor rule response to output gap growth; Smets and Wouters (2007)
ρ	0.80	Persistence in monetary policy; Smets and Wouters (2007)
ρ_a	0.90	Persistence of technology shock; Galí (2011)
ρ_ν	0.50	Persistence of monetary policy shock; Galí (2011), Barnichon (2010)
γ	1.00	*Quadratic hiring cost
ϕ	1.00	*Increasing marginal disutility from effort
ψ	0.50	*Additional curvature of effort in production function

Note: Robustness to the choice of parameters marked by * is available in Appendix H.

Interpreting α as the share of non-labour inputs in the total factor cost of production ($\alpha = 0.33$), the calibration of the additional concavity of the production function in labour effort, ψ is open within certain limits: ψ cannot exceed 0.50 to avoid increasing returns to scale (IRS) as it would be inconsistent with the perfectly competitive nature of the intermediate goods firms considered here.[17] While Gordon (1993) emphasizes the theoretical need for the presence of such increasing returns to labour to explain business cycle facts, empirical finding has been mixed: Basu (1996) does not find significant IRS, but Basu, Fernald and Kimball (2001) have confirmed IRS for durable manufacturing and services industries. Irrespective of the returns to scale, so long as $\psi \in (0, 1)$, the main mechanism of the model will survive because firms will prefer to rely on employment-level changes instead of effort changes in the absence of hiring cost. A similar consideration for the households' disutility from effort and employment requires the degree of increasing marginal disutility from exerting more effort, ϕ to be simply positive for the model intuition to go through. In the baseline calibration of the model, I assume $\psi = 0.5$ for constant returns to scale and $\phi = 1$ but show the robustness to alternative

[17]If $\alpha = 0$, the production function $Y_t = A_t E_t^{\psi} N_t$ can be thought as a special case of a standard Cobb-Douglas production function with effective labour input, $E.N$ and capital K, $\tilde{Y}_t \equiv A_t \left(E_t N_t\right)^{\psi} K_t^{(1-\psi)}$, provided capital per worker, K_t/N_t is held constant over the business cycle, since $\tilde{Y}_t = Y_t \left(K_t/N_t\right)^{1-\psi}$. In this Cobb-Douglas representation, the parameter ψ has the natural interpretation of the labour share in aggregate production, and can, therefore, be calibrated to a value of 0.67. This route of calibration has been adopted in Barnichon (2010).

values in Appendix H.

Finally, the nominal rigidities in the baseline calibration have been assumed to have remained constant across the pre and post-1984 periods. However, Smets and Wouters (2007) find a significant rise in the price rigidity for goods in the post-1984 period because of the reluctance of firms to change prices in an era of low inflation under the Great Moderation. They also find nominal wage rigidity to have gone up after the mid-1980s, although the increase is not statistically significant. Nevertheless, recognizing that increasing nominal wage rigidity can lead to firms relying less on wage changes and more on adjusting employment, which further depresses the procyclicality of productivity and increases the relative employment volatility (see Gu and Prasad (2018)), I show in Appendix Table H.4, that allowing for the price and nominal wage rigidities to change between the two sub-periods according to the estimates in Smets and Wouters (2007) does not qualitatively alter the findings.

4.2 Quantitative Performance of the Model

In Table 4.1, I have considered multiple parameter changes in the calibration for the two sub-periods. To ascertain the role of each parameter change in explaining the main phenomenon of vanishing procyclicality of labour productivity, along with other changes in business cycle moments like the rising relative volatility of employment, the falling procyclicality of real wages, etc., I introduce them one at a time.

De-unionization — In Table 4.3, I show how de-unionization alone performs in capturing the changes in the moments. Column (1) reports the empirically observed changes in business cycle moments between pre and post-1984 periods, while column (4) reports the total change explained by de-unionization. Comparing these one finds the parameter changes attributed to de-unionization perform quite well in matching the empirically observed drop in productivity correlations, both for unconditional correlations as well as conditional on technology and demand shocks. For the relative volatility of employment, the baseline calibration of the model captures more than 75% of the total rise in the data.

A fall in union density is captured by changes in two parameters: a fall in the share of hiring cost in GDP, Θ and a rise in the firms' bargaining power, ξ. I show the relative contribution of these two channels in columns (2) and (3) respectively. While most of the changes in the productivity correlations and relative volatility of employment can be attributed to the change in the hiring cost parameter (which is the central mechanism highlighted in this paper), the model's ability to capture the changes in the cyclical wage correlations is primarily driven by the change in the bargaining power parameter. This importance of the bargaining parameter in determining wage dynamics is not surprising, given that the parameter directly enters the real wage equation (3.13).

Regarding the volatility of real wages, while the current model predicts a fall in the post-1984 era (not shown here), empirical evidence on wage volatility has been mixed. Champagne, Kurmann and Stewart (2017) discuss how average hourly wage volatility in the U.S. has diverged across different data sources: the BLS-LPC, CPS, and the Current Employment Statistics (CES). Supplements and

Table 4.3: Changes in Business Cycle Moments due to De-unionization

Business Cycle Moments	**Changes in Moments between Pre- & Post-1984**			
		Model		
	Data (1)	Hiring Cost: Θ (2)	Bargaining Power: ξ (3)	Unions: Θ, ξ (4)
ALP Correlations				
Output: $Corr\,(y_t, alp_t)$	-0.40	-0.54	-0.08	-0.58
Employment: $Corr\,(n_t, alp_t)$	-0.51	-0.35	-0.07	-0.38
Hiring Flows: $Corr\,(h_t, alp_t)$	-0.53	-0.48	-0.04	-0.50
Volatility of Employment				
Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+46%	+35%	+6%	+38%
Conditional $Corr\,(n_t, alp_t)$				
Technology Shock	-0.06	-0.06	-0.03	-0.07
Demand Shock	-1.24	-0.58	-0.10	-0.59
Conditional $Corr\,(y_t, alp_t)$				
Technology Shock	+0.19	-0.08	-0.01	-0.09
Demand Shock	-1.21	-0.89	-0.11	-0.91
Real Wage Correlations				
Output: $Corr\,(y_t, w_t)$	-0.34	-0.06	-0.72	-0.41
Employment: $Corr\,(n_t, w_t)$	-0.34	-0.11	-0.77	-0.50
ALP: $Corr\,(alp_t, w_t)$	-0.10	-0.12	+0.13	+0.12

Note: All columns report changes in moments of HP-filtered variables between pre and post-1984 periods. Column (1) reports the empirically observed changes in the business cycle moments. Column (2) reports the changes in the model-implied moments when only the hiring cost parameter Θ is allowed to drop from 3% to 1%. Similarly, column (3) allows only the wage bargaining power parameter ξ to increase from 0.50 to 0.84. Column (4) combines the two parameter changes in columns (2) and (3) for the total change due to de-unionization.

irregular earnings of high-income workers, included only in the LPC, drive the rising volatility in LPC earnings as opposed to CPS and CES based measures. One way to match the rising volatility of real wages (e.g., Champagne and Kurmann (2013) and Nucci and Riggi (2013)) in the current model would be to introduce real wage rigidity (through wage indexation to past inflation, or though endogenous rigidity that depends on the size of the wage bargaining set in equilibrium) and let it decline in the post-1984 period. These channels are however absent in the current version of the model and remain a task for future research.

Accommodative Monetary Policy — In Table 4.4, column (3) shows that more accommodative monetary policy by the Federal Reserve cannot induce large changes in the productivity moments, and most of those changes go against the empirically observed direction of moment changes. As argued in Section 2.2.3, allowing for a more accommodating monetary policy means that conditional on a positive technology shock when output gap increases, the contraction induced through monetary policy is less severe. This implies that with a lower ϕ_y, the productivity correlations conditional on a technology shock are higher. This corroborates the empirical finding in Section 2.2.3 that the negative impulse response of hours worked to a positive technology shock is muted after the mid-1980s. To summarize, in the absence of the more accommodative stance of the Federal Reserve under Volcker, the drop in productivity correlations would have been even more severe.

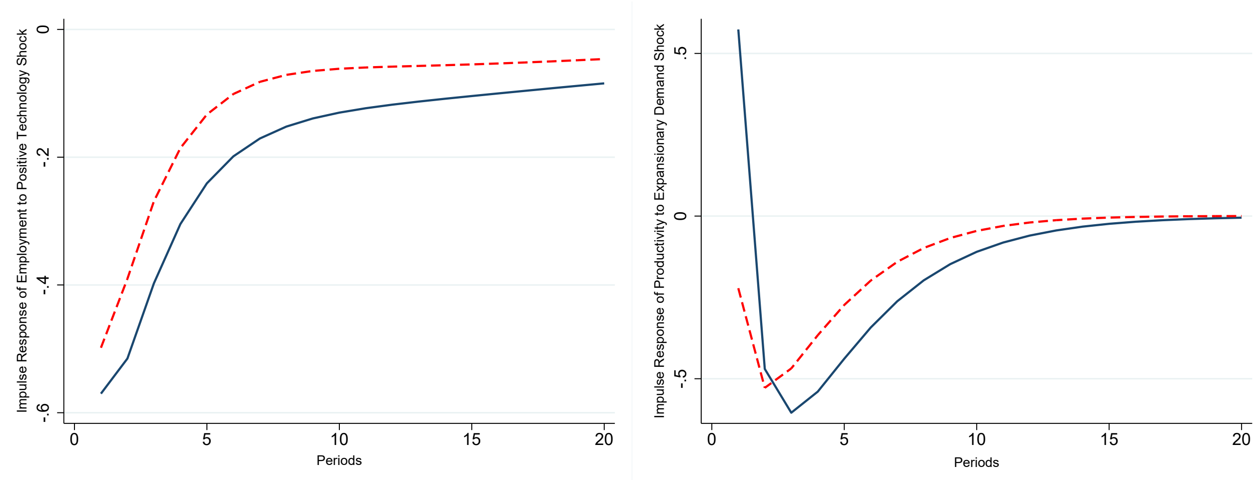
Reduction in Shock Volatility — Column (4) of Table 4.4 shows that the model's ability to match the changes in the business cycle moments is not contingent on the drop in volatilities of the exogenous shocks during the Great Moderation. There are two aspects to this observation. First, a uniform reduction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

The finding that a fall in productivity correlations conditional on a demand shock is driving the unconditional moments implies that demand shock must be the main source of variation for output and employment dynamics over the business cycle. This has been empirically corroborated by many authors, starting from Burnside, Eichenbaum and Rebelo (1993). Since the only non-technology shock in the model is the monetary policy shock, it is the dominant source of business cycle variation here. However, Smets and Wouters (2007) find that in the presence of a variety of demand shocks, e.g., exogenous spending shock, risk premium shock, investment-specific technology shock, etc., the role of monetary policy shock is quite limited in the cyclical variation of output. Thus, the predominant role played by the monetary policy shock in this model should be thought of as a consequence of the loading of all variation due to various demand shocks onto a single monetary policy shock.

Table 4.4: Changes in Business Cycle Moments between Pre- and Post-1984

Business Cycle Moments	**Changes in Moments between Pre- & Post-1984**			
		Model		
	Data (1)	Unions (2)	Monetary Policy: ϕ_y (3)	Shocks: σ_a,σ_ν (4)
ALP Correlations				
Output: $Corr\,(y_t, alp_t)$	-0.40	-0.58	-0.01	+0.09
Employment: $Corr\,(n_t, alp_t)$	-0.51	-0.38	+0.03	-0.04
Hiring Flows: $Corr\,(h_t, alp_t)$	-0.53	-0.50	+0.05	-0.10
Volatility of Employment				
Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+46%	+38%	-1%	-2%
Conditional $\boldsymbol{Corr\,(n_t, alp_t)}$				
Technology Shock	-0.06	-0.07	+0.05	0.00
Demand Shock	-1.24	-0.59	-0.01	0.00
Conditional $\boldsymbol{Corr\,(y_t, alp_t)}$				
Technology Shock	+0.19	-0.09	+0.04	0.00
Demand Shock	-1.21	-0.91	-0.01	0.00
Real Wage Correlations				
Output: $Corr\,(y_t, w_t)$	-0.34	-0.41	+0.02	-0.00
Employment: $Corr\,(n_t, w_t)$	-0.34	-0.50	+0.09	-0.16
ALP: $Corr\,(alp_t, w_t)$	-0.10	+0.12	-0.08	+0.15

Note: All columns report changes in moments of HP-filtered variables between pre and post-1984 periods for both data and model-simulated series. Column (1) reports the empirically observed changes in the business cycle moments. Column (2) refers to the total effect of de-unionization by allowing the parameters Θ and ξ to change, same as column (4) in Table 4.3. Column (3) allows only the Taylor rule parameter ϕ_y to drop from 0.17 to 0.08. Similarly, column (4) corresponds to the changes in model-implied moments when only the volatilities of the shocks are allowed to decrease in the post-1984 period according to the calibration in Table 4.1.



(a) Technology Shock: Employment

(b) Demand Shock: ALP

Figure 4.1: Model-implied Impulse Responses to Technology and Demand Shocks
Note: Model-generated IRFs for pre-1984 (blue solid line) and post-1984 (red dashed line) are based on parameter calibrations in Tables 4.1 and 4.2. Both technology and demand shocks are expansionary, i.e., one standard deviation increase in a_t and decrease in ν_t.

When all the parameters in Table 4.1 are allowed to change simultaneously between the pre and post-1984 periods, the model can generate impulse responses that are in line with the empirically observed ones in Section 2.2.3. Figure 4.1 shows how the impulse response of employment rate to a positive technology shock (panel (a)), and that of average labour productivity to an expansionary monetary policy shock (panel (b)) have both become muted in the post-1984 period. While the muted negative response of employment to technology shock is almost entirely driven by the fall in ϕ_y, the reduced magnitude of the rise in productivity due to a negative interest rate shock is caused by the fall in hiring cost Θ. These changes in impulse responses once again prove that the labour productivity puzzle cannot be explained by the rise in the relative importance of the technology shock, but rather by structural changes in the economy that caused productivity to increase less or even decrease to positive demand shocks over the business cycle.

5 Other Plausible Explanations: Lack of Evidence

Having shown that lower employment adjustment cost due to de-unionization can quantitatively account for the productivity puzzle in the U.S., I now argue that some other potential explanations do not hold up to empirical scrutiny.

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 bad times, 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

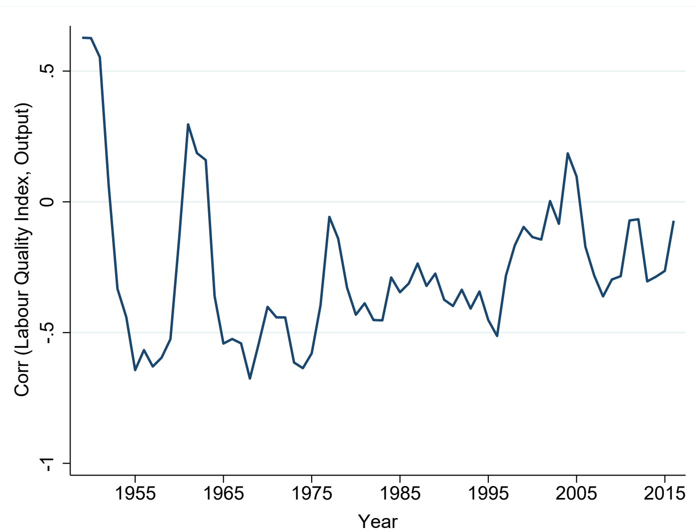


Figure 5.1: Cyclical Correlation of Labour Quality Index with Output
Note: Labour Quality Index and output data for U.S. business sector is sourced from Fernald (2014).

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, see Berger (2016)), then it could explain the productivity puzzle.

To ascertain whether this is indeed the case, I compute the cyclical correlation of a measure of labour quality with business sector output. 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).[18] Plotting the rolling window correlation of labour quality and 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). This implies that the greater ease of hiring and firing workers did not translate into a more selective firing of low-quality workers during recessions (at least for a measure of quality that is observable in macro data), but rather more hiring and firing in general of all workers (or the 'average-quality representative' worker).

[18]This analysis is limited by the possibility that firms have more information on individual worker productivity than is measured by the Labour Quality Index.

5.2 Rise of the Service Sector

The rise of the service sector can have a *composition effect* on the cyclical correlations of productivity: 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 or employment towards services can explain the decline in the aggregate productivity correlations. However, the labour productivity correlations in Table 5.1 clearly show that the two sectors had strikingly similar correlations even before the mid-1980s, and both of them experienced a similar drop in labour productivity correlations over the business cycle. Moreover, this compositional shift towards services has been too gradual to explain the sudden drop in the productivity correlations.

Table 5.1: Labour Productivity Correlations 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 annual KLEMS dataset between 1947 and 2010 by aggregating industry-level non-additive chained indices according to the cyclical expansion method developed in Cassing (1996). Results are robust to using annual sectoral dataset from BEA, compiled by Herrendorf, Herrington and Valentinyi (2015).

The 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 the labour productivity of all sectors will mimic that of the services sector.[19] While all industries, except agriculture, 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 change 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 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

[19] This idea of evolving input-output structure of the economy leading to switch in the cyclicality of productivity can be found in Huang, Liu and Phaneuf (2004), who explain the switch in the cyclicality of real wages in the post-War period.

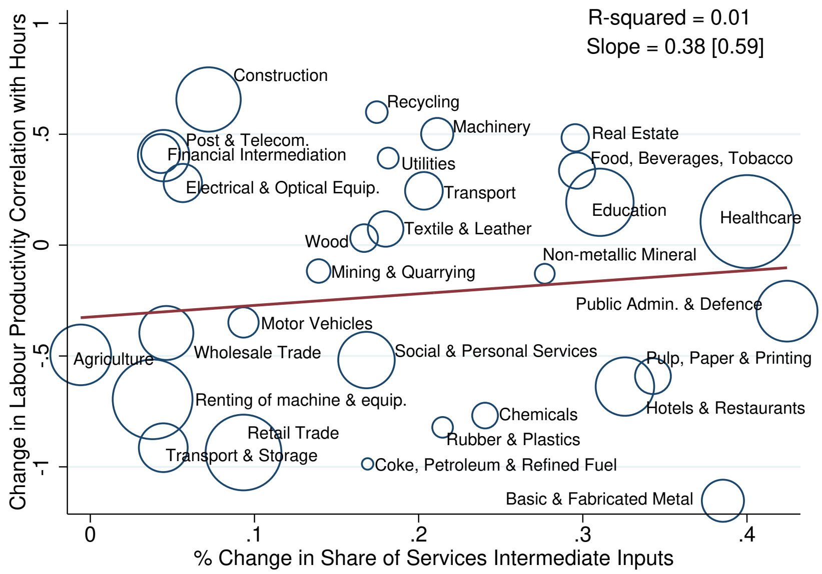


Figure 5.2: Services Intermediate Input Share & Productivity Correlation

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. Result is robust to using other filters.

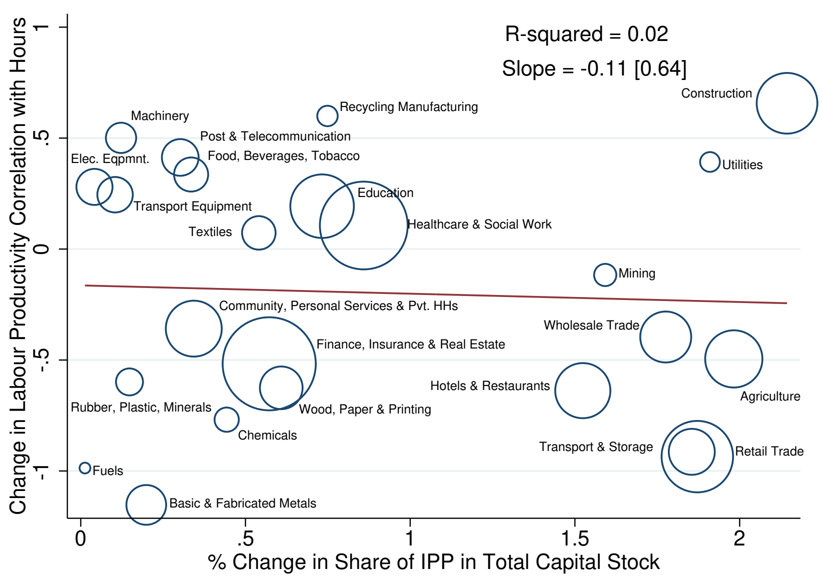


Figure 5.3: Share of IPP Capital & Productivity Correlation

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

supported by the data when the correct time-period is considered. Specifically, I want to check if the rise in intangible investment across U.S. industries around the mid-1980s is positively correlated with the magnitude of the fall in cyclical productivity correlation.

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."* Keeping this definition in mind, any empirical measure of intangible investment is difficult to find, but the closest in available data is investment in intellectual property products (IPP). IPP contains research and development, computer software and databases, and other products like artistic originals.[20] While IPP investment picked up in the late 1970s and early 1980s across almost all industries, I do not find a significant correlation between the rise in IPP capital share and the drop in labour productivity correlations in the cross-section (see Figure 5.3).

5.4 Aggregate versus Sectoral Shocks

Aggregate productivity can be boosted through reallocation of factors of production towards firms and industries with higher marginal products of inputs (see Hsieh and Klenow (2009)). Thus, if frictions impeding the efficient allocation of resources has become less important during economic downturns 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 but 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 use an alternative measure of sectoral reallocation developed by Rissman (1997), and show that reallocation of employment across industries has declined over the recent business cycles. This casts doubt on the productivity-enhancing sectoral reallocation narrative of explaining the productivity puzzle.

Garin, Pries and Sims (2018), however, differ. Using the finding in Foerster, Sarte and Watson (2011) that sectoral reallocation shocks became more important for business cycles in the U.S. economy over recent years, they claim that more efficient reallocation in the post-1984 period has led to less procyclical productivity. Their claim hinges crucially on the empirical finding that the volatility of aggregate economy-wide shocks has shrunk drastically in the post-1984 era relative to sector-specific shocks across 12 manufacturing industries from the Index of Industrial Production (IIP). I replicate their analysis using industry-level data from various sources — BEA, CES, IIP and KLEMS. Not only is there considerable heterogeneity across datasets in how much of the total variation in output and hours growth is explained by sectoral shocks, but even the main finding of sectoral shocks becoming more important is not robust to the number of industry classifications. For example, when the 31-industry classification from KLEMS dataset or the 20-industry classification from IIP data (in-

[20] See Appendix I for a detailed discussion on the measure of IPP capital.

stead of the 12-industry classification in Garin, Pries and Sims (2018)) is considered, there is no clear pattern of sectoral reallocation shocks becoming more important in the later decades.[21] Moreover, sectoral measures of productivity already take into account the intra-industry inter-firm reallocation of resources. Since a majority of U.S. industries has individually experienced a decline in procyclicality of productivity (as shown in Section 2), it is likely that intra-industry factor reallocation across firms has been more important than inter-industry reallocation for explaining the productivity puzzle. Thus, the evidence for increased inter-sectoral labour reallocation as an important explanation for the vanishing procyclicality of productivity appears less than convincing.

6 Conclusion

Lower dependence on labour hoarding by firms caused productivity to lose its procyclicality in the mid-1980s in the U.S. With lower costs of hiring and firing workers due to a rapid decline in labour union power, firms started relying more on adjusting labour input through the extensive margin rather than changing workers' effort along the business cycle. Cross-sectional evidence from OECD countries and U.S. states and industries showed that de-unionization could predict both the loss in procyclicality of productivity and the rising volatility of employment relative to that of output. A New Keynesian model with endogenous effort choice and a time-varying cost of hiring workers was shown to be able not only to generate the empirically observed changes in the business cycle moments of output, employment and productivity but also to match qualitatively the changes in the impulse responses of these variables to technology and demand shocks. Moreover, other plausible explanations for the productivity puzzle, e.g., the increased firing of less productive workers during recessions, the rise of the service sector, the increased use of intangible capital, and the increased productivity-enhancing factor reallocation during recessions, were shown to have little to no empirical validity.

A world with less procyclical productivity and higher relative volatility of employment brings instability in workers' jobs. Immediate 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 (2018) show that such policies in Italy stabilized employment and brought small positive welfare gains during the Great Recession. Graves (2019) 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 policymaking in a world with countercyclical productivity.

[21] See Appendix J for details of analysis showing the relative importance of sector-specific shocks.

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Appendix

A Robustness 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.

Since the TFP data is only available in growth rates, I could only use quarterly and annual growth rates as the filter for the analysis involving TFP. For other variables, apart from 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	-0.17	-0.52	-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	Post-1984	$\frac{Post}{Pre}$	s.d.(Hours) Pre-1983	Post-1984	$\frac{Post}{Pre}$	s.d.(Employment) Pre-1983	Post-1984	$\frac{Post}{Pre}$
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

Dataset & Filter	$\frac{s.d.(Hours)}{s.d.(Output)}$ Pre-1983	Post-1984	$\frac{Post}{Pre}$	$\frac{s.d.(Employment)}{s.d.(Output)}$ Pre-1983	Post-1984	$\frac{Post}{Pre}$	$\frac{s.d.(Employment)}{s.d.(Hours/Worker)}$ Pre-1983	Post-1984	$\frac{Post}{Pre}$
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

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

Utilization Rates	Corr. with Output Pre-1983	Post-1984	Change	Corr. with Hours Pre-1983	Post-1984	Change	Variance Pre-1983	Post-1984	Change
Factor Util.	0.73	0.49	- 0.24	0.67	0.52	- 0.15	11.67	1.64	-85.9%
Capacity Util.	0.86	0.61	- 0.25	0.89	0.64	- 0.25	8.28	4.73	-42.9%

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 0.73.

B 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.[22] 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.[23] 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 $x_t \equiv [\Delta(y_t - n_t), n_t]$, where y_t and n_t denote the (log) output and (log) hours in per capita terms, the reduced form VAR can be written as:

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

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 (B.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-

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

[23] 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 B.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 B.3.

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

$$\ln\left(hours_t/pop_t\right) = \alpha_h + \beta_h \Delta \ln\left(uatfp_t\right) + \theta_h\left(L\right) X_{t-1} + \varepsilon_{t+h} \tag{B.2}$$

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

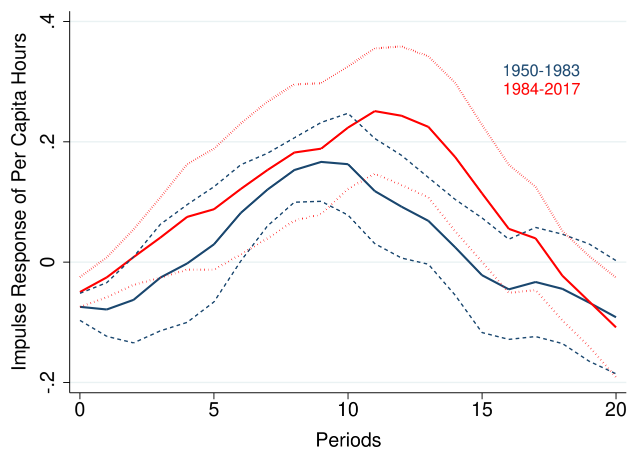
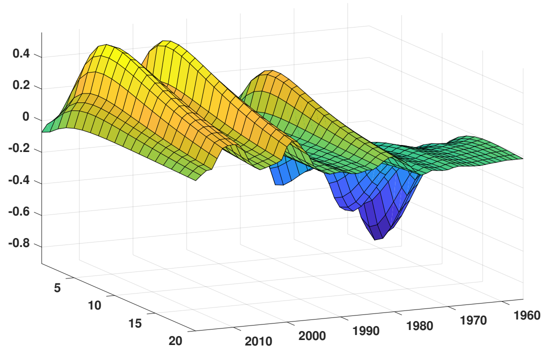


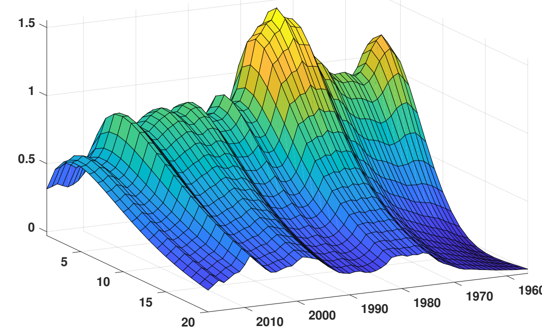
Figure B.1: IRF of Per Capita Hours to Utilization-Adjusted TFP Shock

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).

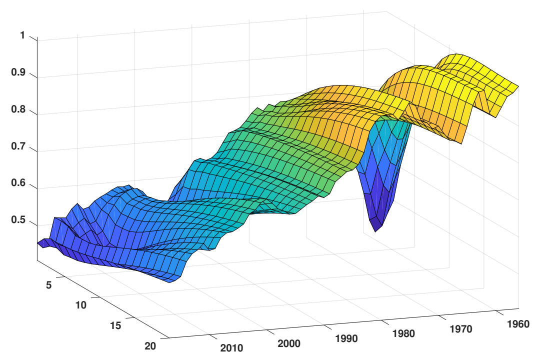
This methodology of a simple regression model with the shock being the explanatory variable not only shows the negative correlation of hours and technology shock but also that the negative response of hours became muted after the mid-1980s (see Figure B.1).



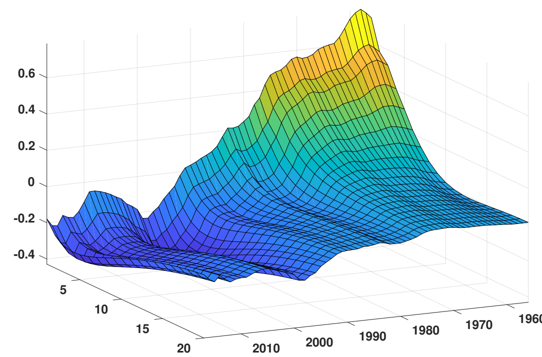
(a) Technology Shock: Hours



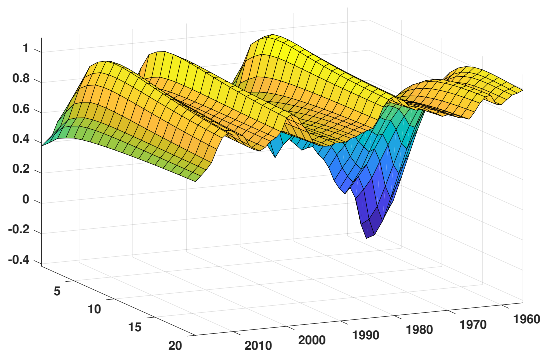
(b) Demand Shock: Hours



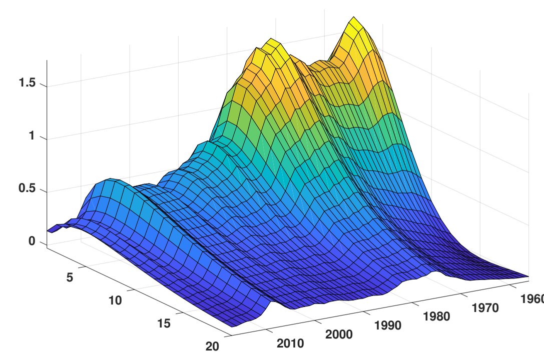
(c) Technology Shock: Labour Productivity



(d) Demand Shock: Labour Productivity



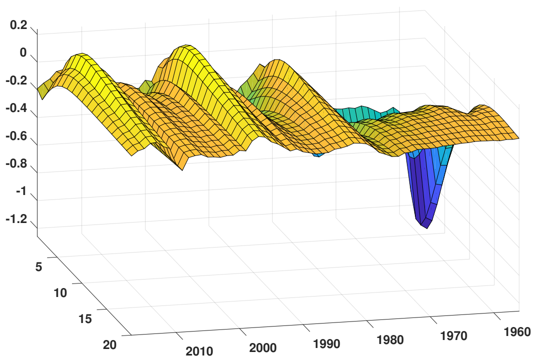
(e) Technology Shock: Output



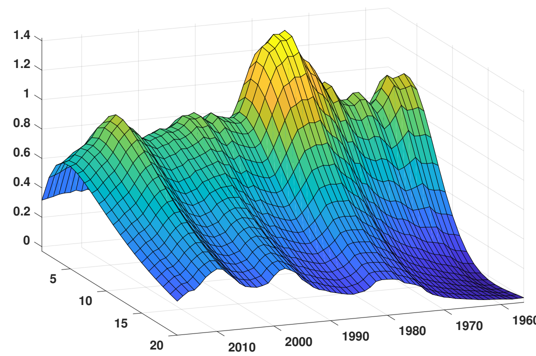
(f) Demand Shock: Output

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

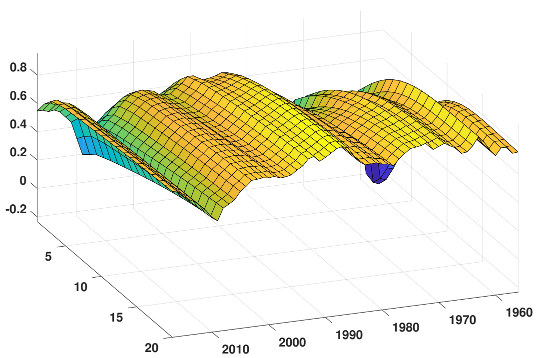
Note: Impulse Response Functions of per-capita hours, labour productivity and per-capita output from a 2-variable (viz., labour productivity growth and per-capita hours) time-varying long-run SVAR. Data is sourced from the BLS-LPC quarterly dataset for the U.S. business sector. Quarterly civilian non-institutional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



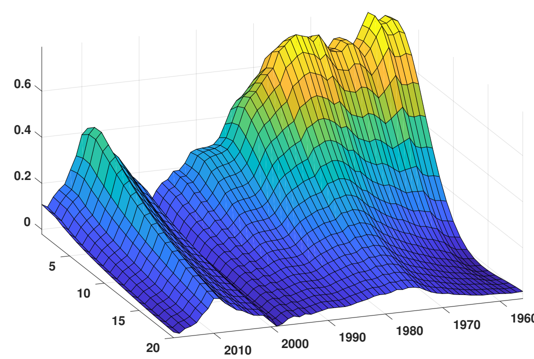
(a) Technology Shock: Hours



(b) Demand Shock: Hours



(c) Technology Shock: TFP



(d) Demand Shock: TFP

Figure B.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.

C Plausible Channels of Increased Labour Market Flexibility

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

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

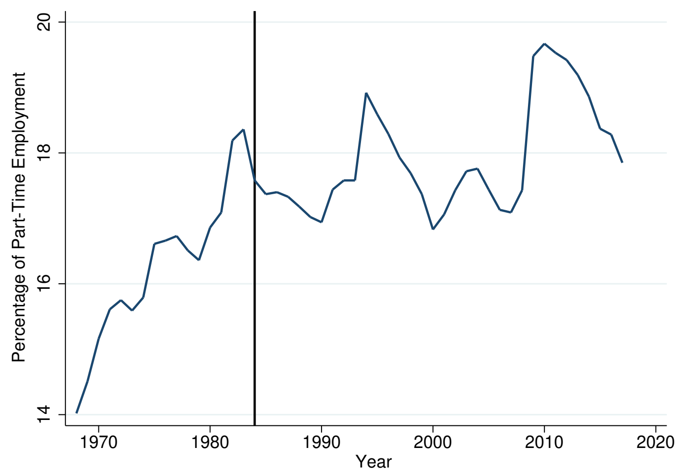


Figure C.1: Share of Part-time Employment in the U.S. (1968-2017)

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

For the U.S. it is difficult to ascertain the role of temporary workers in the increased flexibility of labour markets due to lack of suitable data that dates back long enough, e.g., employment data for the temporary help services industry from the Current Employment Statistics (CES) database of BLS dates back only till 1990. Although Carey and Hazelbaker (1986) show that employment growth in the temporary help industry increased sharply immediately after the 1982 recession, which lines up well with the timing of the switch in labour productivity correlations, Schreft and Singh (2003) show that temporary and part-time hiring and overtime — collectively known as 'just-in-time hiring' — has gained in importance only since the 1991 recession in the U.S. However, for the U.S., I study the time series of the share of part-time workers (see Figure C.1) and do not find any noticeable upsurge, if not an actual plateauing, in the share of part-time workers around the mid-1980s.

In Table C.1, I present changes between the pre and post-1984 periods in the cyclical properties of some labour market variables from selected OECD countries. The cyclical moments reported are changes in (i) correlation of labour productivity with output, (ii) correlation of labour productivity with hours worked, and (iii) relative volatility of employment to output. Variables capturing labour market structure are changes in (i) employment protection laws as measured by the OECD EPRC index, and (ii) gross job separation rate.

Table C.1: Labour Market Statistics from OECD Countries

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

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

Galí and van Rens (2020) 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 much less new workers to maintain the level of employment. This reduced hiring activity implies lower cost of employment adjustment in equilibrium, thereby leading to more countercyclical productivity. While this channel of reduction in employment adjustment cost is feasible for the U.S., the international evidence in Table C.1 does not support a decrease in job separation rate as a common cause for reduced procyclicality of productivity. 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. Moreover, even for the U.S., looking at job flows data from Shimer (2012), I do not find any substantial drop in job separation rate around 1983. Table C.2 shows the averages of 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 C.2: 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).

D 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. To argue for this causal channel, I follow a difference-in-difference regression strategy similar to Card (1992). I consider a very simple structural model that explains the fall in employment adjustment cost in industry i, $\Delta Cost_i$, 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, $\Delta Corr\,(lp_i, h_i)$, as a function of that change in cost:

$$\Delta Cost_i = a + bUnion_i^{pre} + e_i \tag{D.1}$$

$$\Delta Corr\,(lp_i, h_i) = \alpha + \beta \Delta Cost_i + \varepsilon_i \tag{D.2}$$

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

$$\begin{aligned} \Delta Corr\,(lp_i, h_i) &= (\alpha + a\beta) + b\beta Union_i^{pre} + (\beta e_i + \varepsilon_i) \\ \implies \Delta Corr\,(lp_i, h_i) &\equiv \beta_0 + \beta_1 Union_i^{pre} + \eta_i \end{aligned} \tag{D.3}$$

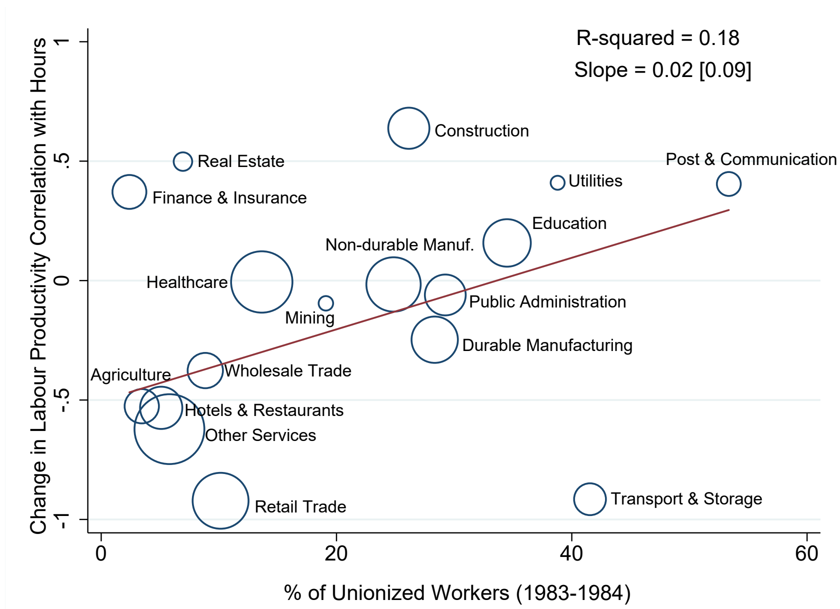
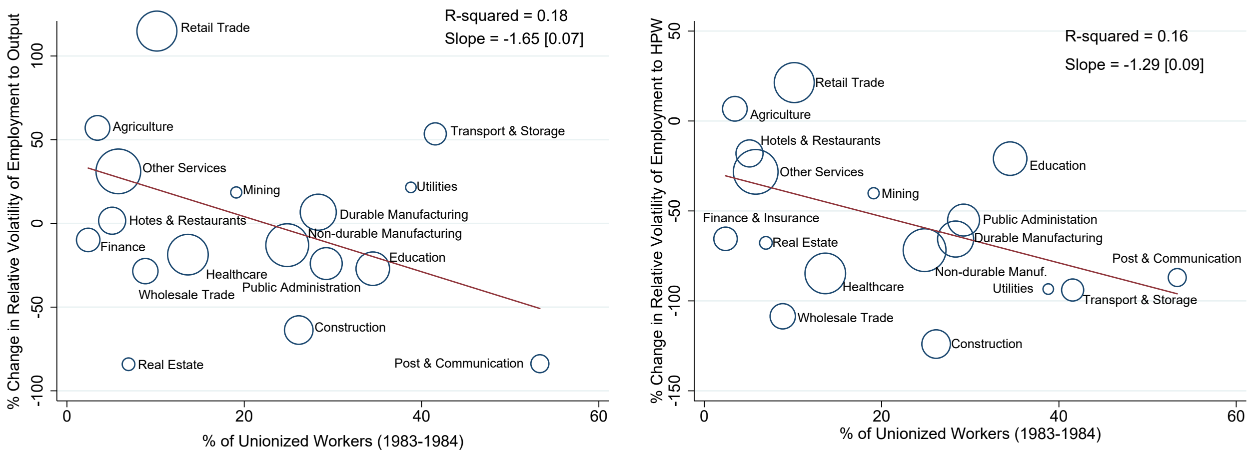


Figure D.1: Effect of Union Density on Productivity Correlation

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 (D.3) can be interpreted as showing the impact on productivity correlations in different industries which were differentially impacted by de-unionization. In other words, if one thinks of the fall in union rates around the early 1980s as the treatment, then the intensity of treatment varied across industries according to the pre-intervention level of union densities in those industries. In particular, an industry with a higher pre-intervention level of union density should be impacted more by the de-unionization treatment, thereby leading to a larger fall in productivity correlations. As an extreme example, an industry with no unionization to begin with will experience no impact of the de-unionization event. Running the regression in equation (D.3) across 17 U.S. industries, I find a significant positive effect of union density on the fall in productivity correlation, as shown in Figure D.1. In order to avoid small industries driving the correlation pattern, I weighted the observations by the pre-1983 average industry employment level.



(a) Relative to Output Volatility

(b) Relative to Hours Per Worker Volatility

Figure D.2: 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.

Finally, replacing the change in productivity correlations by the change in the relative volatility of employment in equation (D.3), I find that industries with a larger pre-1984 level of union density experienced a larger increase (or a smaller decrease) in the volatility of employment relative to that of output and hours per worker. This is shown in Figure D.2.

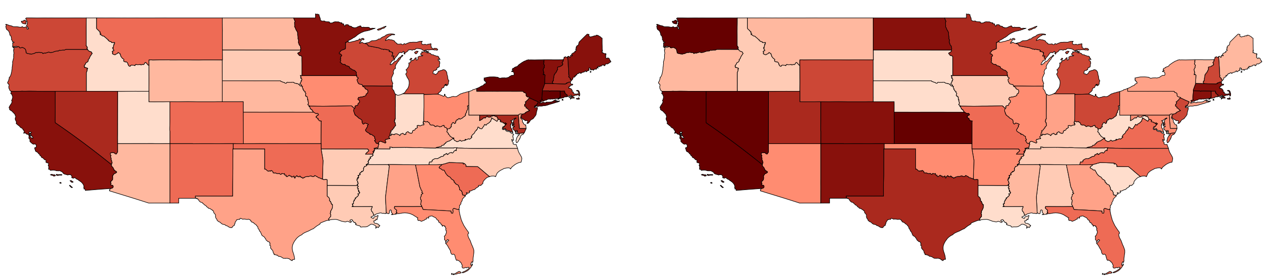
The negative correlation patterns in panels (a) and (b) of Figure D.2 are similar, but there is a subtle difference between the two scatter plots. A lot of the industries experienced a rise in the relative volatility of employment with respect to output, while very few experienced a similar rise in volatility of employment relative to that of hours per worker. This finding that the extensive margin of employment adjustment became less volatile relative to the intensive margin of changing hours per worker in almost all industries is an apparent aberration from what one would expect under falling employment adjustment cost.[24] This is particularly puzzling in light of the evidence in Figure 2.3c that employment became increasingly more volatile relative to factor utilization since the

[24]The post-1984 change in the volatility of employment relative to that of hours per worker is not very robust to the choice of different datasets and time-series filters (see Table A.3 in Appendix). Regardless of the filter used, the volatility of employment relative to hours per worker did not show any stark upward trend after the mid-1980s.

1980s. To understand why the dynamics of hours per worker and factor utilization might vary, it is instructive to study the industry-level differences in the elasticity of output with respect to hours per worker. Basu, Fernald and Kimball (2001) find that the responsiveness of output to hours per worker is vastly different across industry-groups, e.g., the non-durables manufacturing sector is roughly 60% more responsive than the durables manufacturing industries, and more than 3 times as responsive as the service sector. The declining share of manufacturing in the U.S. can therefore explain the larger decline in volatility of factor utilization at the aggregate level than within individual industries.

E Evidence for De-unionization across U.S. States

The following two maps of mainland U.S. in Figure E.1 group 49 U.S. states (the states of Alaska and Hawaii are missing) into deciles, according to (i) the percentage change in unionization between the average union densities in the pre and post-1984 periods, and (ii) the change in correlation between employment growth and output per worker growth in the pre and post-1984 periods.



(a) De-unionization

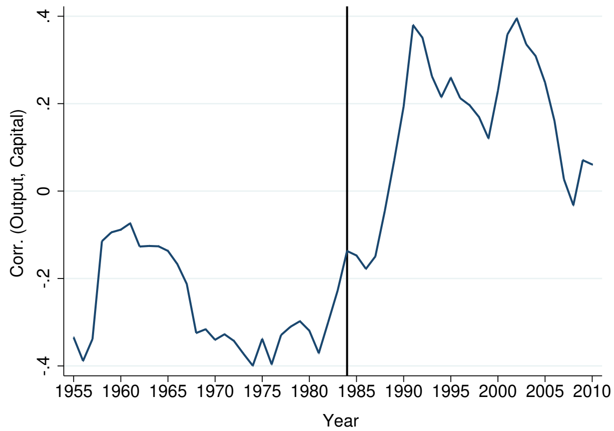
(b) Productivity Puzzle

Figure E.1: De-unionization & Vanishing Procyclicality of Productivity in U.S. States

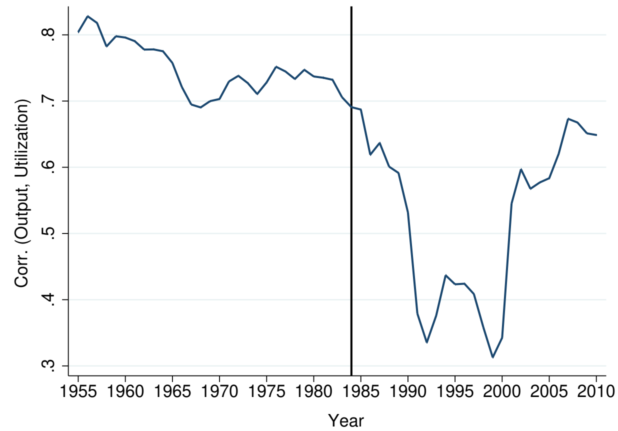
Note: Lighter shades correspond to a larger percentage decline in union density in panel (a), and to a larger decrease in labour productivity correlation with employment in panel (b).

F Cyclical Moments of Capital and Factor Utilization

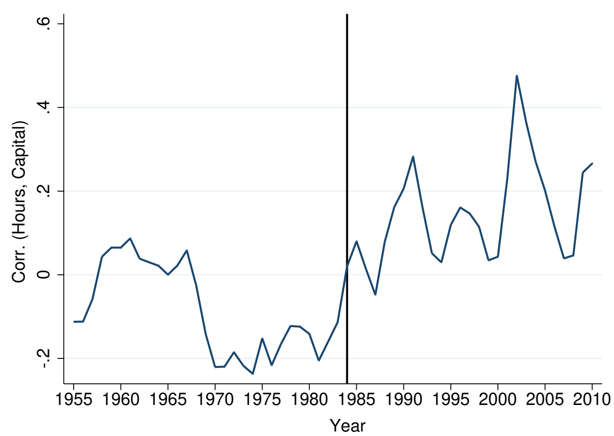
The model in this paper does not feature capital, rather includes only employment and effort. Since labour effort is not directly measurable in the data, one concern is that whatever is being labelled as 'effort' in the model is essentially capital, the missing factor of production. Therefore, it is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



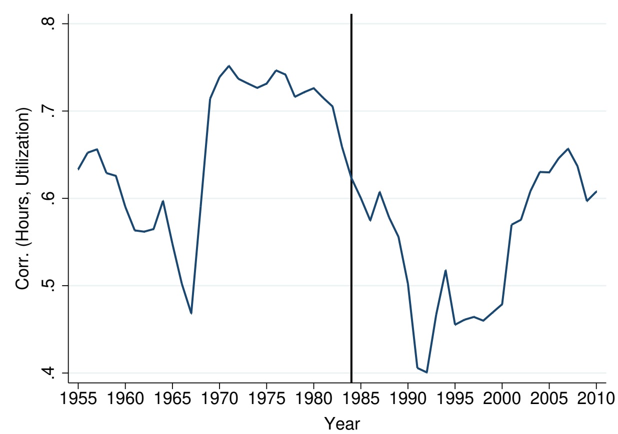
(a) Corr.(Output,Capital)



(b) Corr.(Output,Utilization)



(c) Corr.(Hours,Capital)

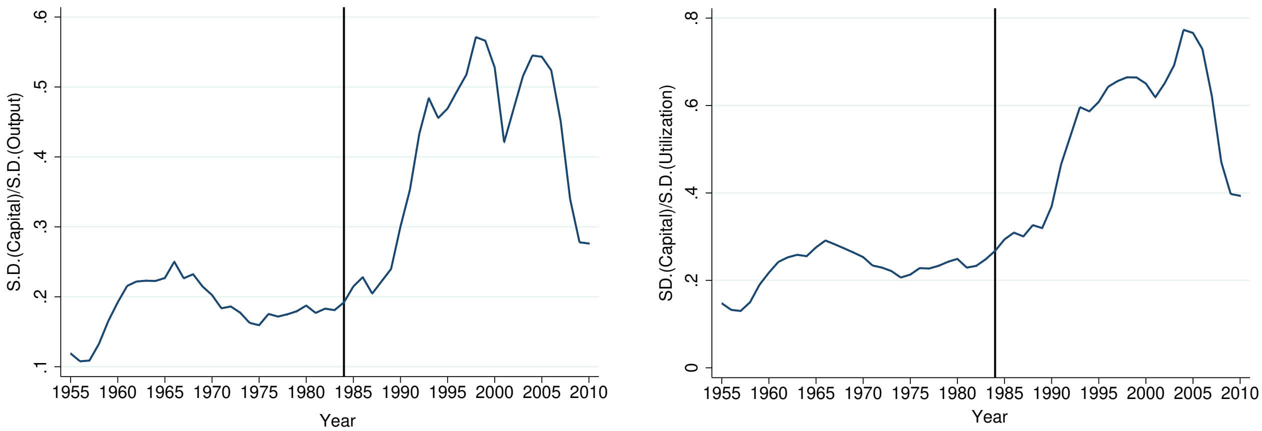


(d) Corr.(Hours,Utilization)

Figure F.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 F.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 F.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 (4) of Table 4.3), correlation of effort with labour productivity fell by 0.37, which is qualitatively similar to that of factor utilization.



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

Figure F.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.

G System of log-linearized equations

Log-linearizing the model around a zero-inflation ($\bar{\pi^p} = 0$) steady state with unit effort $\left(\bar{E} = 1\right)$ and employment rate, $\bar{N} = 0.62$, I get the following equations in log-deviation form, where the notation $\hat{x}_t$ is used to denote the deviation of logarithm of the variable X_t from its logged steady state value $\bar{x}$.

$$\hat{y}_t = (1-\Theta)\,\hat{c}_t + \Theta\left(\hat{h}_t + \hat{g}_t\right) \tag{G.1}$$

$$\hat{y}_t = a_t + (1-\alpha)\left(\hat{n}_t + \psi\hat{e}_t\right) \tag{G.2}$$

$$\hat{n}_t = (1-\delta)\,\hat{n}_{t-1} + \delta\hat{h}_t \tag{G.3}$$

$$\hat{g}_t = \gamma\hat{h}_t \tag{G.4}$$

$$\hat{c}_t = \mathbb{E}_t\left(\hat{c}_{t+1}\right) - \hat{r}_t \tag{G.5}$$

$$\hat{r}_t = \hat{i}_t - \mathbb{E}_t\left(\pi^p_{t+1}\right) \tag{G.6}$$

$$\pi^p_t = \beta\mathbb{E}_t\left(\pi^p_{t+1}\right) - \lambda_p\hat{\mu}^p_t \tag{G.7}$$

$$\hat{\mu}^p_t = \left(\hat{y}_t - \hat{n}_t\right) - \left[(1-\Phi)\,\hat{\omega}_t + \Phi\hat{b}_t\right] \tag{G.8}$$

$$\hat{b}_t = \frac{1}{1-\beta(1-\delta)}\hat{g}_t - \frac{\beta(1-\delta)}{1-\beta(1-\delta)}\left[\mathbb{E}_t\left(\hat{g}_{t+1}\right) - \hat{r}_t\right] \tag{G.9}$$

$$\widehat{mrs}_t = \kappa\hat{c}_t + (1-\kappa)\left[\left(\hat{y}_t - \hat{n}_t - \hat{\mu}^p_t\right) + \frac{\iota}{1-\iota}\left(\hat{\omega}_t + \hat{n}_t - \hat{c}_t\right)\right] \tag{G.10}$$

$$\hat{\omega}_t = \hat{\omega}_{t-1} + \pi^w_t - \pi^p_t \tag{G.11}$$

$$\pi^w_t = \beta(1-\delta)\,\mathbb{E}_t\left(\pi^w_{t+1}\right) - \lambda_w\left(\hat{\omega}_t - \hat{\omega}^{target}_t\right) \tag{G.12}$$

$$\hat{\omega}^{target}_t = \Upsilon\widehat{mrs}_t + (1-\Upsilon)\left(\hat{y}_t - \hat{n}_t - \hat{\mu}^p_t\right) \tag{G.13}$$

$$\hat{i}_t = \rho\hat{i}_{t-1} + (1-\rho)\left(\phi_\pi\pi^p_t + \phi_y\hat{y}_t\right) + \phi_{\Delta y}\Delta\hat{y}_t + \nu_t \tag{G.14}$$

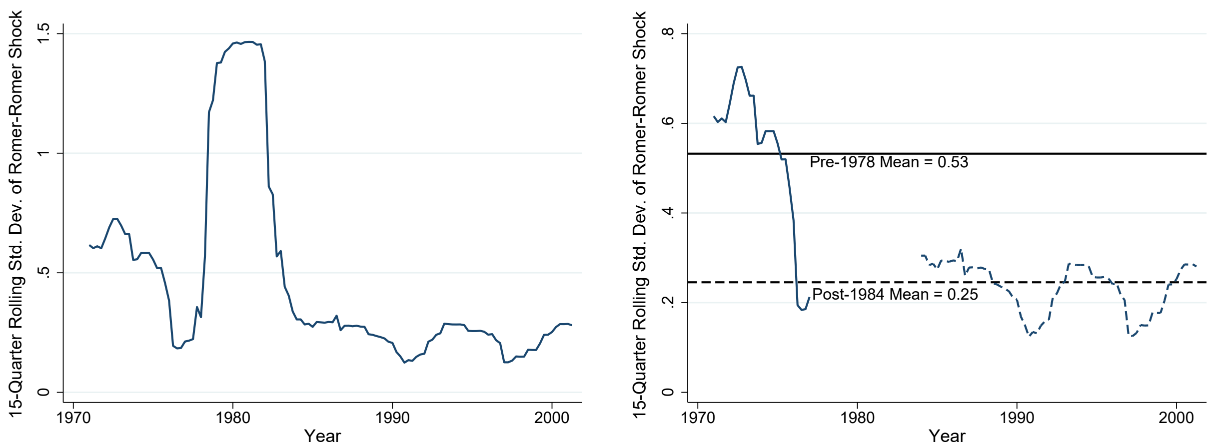
$$\hat{e}_t = \frac{1}{1+\phi}\left(\hat{y}_t - \hat{n}_t - \hat{\mu}^p_t - \hat{c}_t\right) \tag{G.15}$$

$$a_t = \rho_a a_{t-1} + \varepsilon^a_t \tag{G.16}$$

$$\nu_t = \rho_\nu\nu_{t-1} + \varepsilon^\nu_t \tag{G.17}$$

where $\Theta = \frac{\Gamma\left(\delta\bar{N}\right)^{1+\gamma}}{\bar{Y}}$, $\Phi = \frac{\bar{B}}{\bar{B}+\frac{\bar{W}}{\bar{P}}}$, $\kappa = \left(\frac{\chi}{1+\zeta}\right)\cdot\left(\frac{\bar{C}}{\overline{MRS}}\right)$, $\iota = \left(\frac{1+\phi}{1+\phi-\psi}\right)\cdot\left(\frac{\bar{W}\bar{N}}{\bar{P}\bar{C}}\right)$, $\Upsilon = \xi\left(\frac{\overline{MRS}}{\frac{\bar{W}}{\bar{P}}}\right)$, $\lambda_w = \frac{(1-\theta_w)(1-\beta\theta_w(1-\delta))}{\theta_w[1-(1-\Upsilon)(1-\Phi)]}$, and $\hat{\omega}_t = \hat{w}_t - \hat{p}_t$. The parameters ζ and χ are calibrated to satisfy unit effort in the steady-state $\left(\bar{E} = 1\right)$ in a frictionless (no hiring cost) labour market. Furthermore, I take $\frac{\bar{W}\bar{N}}{\bar{P}\bar{C}} = \frac{\bar{W}\bar{N}}{\bar{P}\bar{Y}}\cdot\frac{\bar{Y}}{\bar{C}} = (1-\alpha)\,.\left(\frac{1}{1-\Theta}\right)$.

H Robustness to Calibration

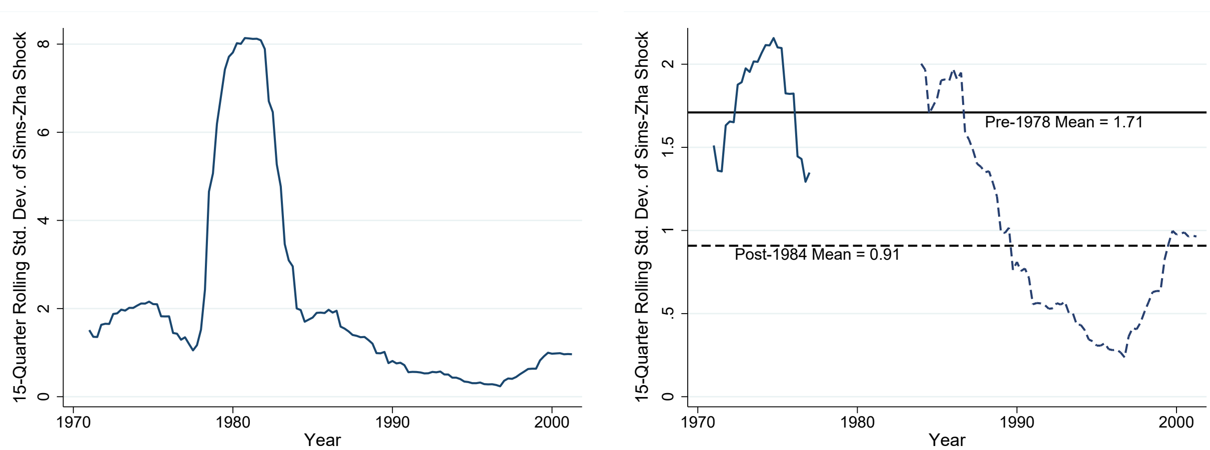


(a) 1971-2000

(b) 1971-1977, 1984-2000

Figure H.1: 15-Quarter Rolling Standard Deviation of Romer-Romer Monetary Shock

Note: Ignoring the sudden jump in volatility in the monetary policy shock between 1977 and 1982 as seen in panel (a), the average standard deviation in the 1984-2000 period is roughly half of that during 1971-1977, as shown in panel (b). Data is sourced from Ramey (2016).



(a) 1971-2000

(b) 1971-1977, 1984-2000

Figure H.2: 15-Quarter Rolling Standard Deviation of Sims-Zha Monetary Shock

Note: Ignoring the sudden jump in volatility in the monetary policy shock between 1977 and 1982 as seen in panel (a), the average standard deviation in the 1984-2005 period is roughly half of that during 1971-1977, as shown in panel (b). Data is sourced from Ramey (2016).

Table H.1: Robustness to Choice of γ

Business Cycle Moments	**Changes in Moments due to De-unionization**		
	$\gamma = 0.6$	Baseline, $\gamma = 1$	$\gamma = 2.4$
	(1)	(2)	(3)
ALP Correlations			
Output: $Corr\,(y_t, alp_t)$	-0.44	-0.58	-0.64
Employment: $Corr\,(n_t, alp_t)$	-0.27	-0.38	-0.49
Hiring Flows: $Corr\,(h_t, alp_t)$	-0.44	-0.50	-0.45
Volatility of Employment			
Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+28%	+38%	+66%
Conditional $\boldsymbol{Corr\,(n_t, alp_t)}$			
Technology Shock	-0.07	-0.07	-0.05
Demand Shock	-0.37	-0.59	-0.74
Conditional $\boldsymbol{Corr\,(y_t, alp_t)}$			
Technology Shock	-0.07	-0.09	-0.08
Demand Shock	-0.63	-0.91	-0.97
Real Wage Correlations			
Output: $Corr\,(y_t, w_t)$	-0.29	-0.41	-0.65
Employment: $Corr\,(n_t, w_t)$	-0.37	-0.50	-0.76
Labour Productivity: $Corr\,(alp_t, w_t)$	+0.12	+0.12	+0.07

Note: All columns report changes in moments of HP-filtered variables between pre and post-1984 periods for alternative values of γ, denoting the degree of convexity of the hiring cost function. All other parameters in the model are fixed at the calibration values used in column (4) of Table 4.3, which corresponds to the total effect of de-unionization.

Table H.2: Robustness to Choice of ϕ

Business Cycle Moments	**Changes in Moments due to De-unionization**		
	$\phi = 0.5$	Baseline, $\phi = 1$	$\phi = 1.5$
	(1)	(2)	(3)
ALP Correlations			
Output: $Corr\,(y_t, alp_t)$	-0.62	-0.58	-0.54
Employment: $Corr\,(n_t, alp_t)$	-0.42	-0.38	-0.35
Hiring Flows: $Corr\,(h_t, alp_t)$	-0.52	-0.50	-0.48
Volatility of Employment			
Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+43%	+38%	+34%
Conditional $Corr\,(n_t, alp_t)$			
Technology Shock	-0.06	-0.07	-0.07
Demand Shock	-0.65	-0.59	-0.54
Conditional $Corr\,(y_t, alp_t)$			
Technology Shock	-0.09	-0.09	-0.09
Demand Shock	-0.97	-0.91	-0.85
Real Wage Correlations			
Output: $Corr\,(y_t, w_t)$	-0.38	-0.41	-0.42
Employment: $Corr\,(n_t, w_t)$	-0.48	-0.50	-0.50
Labour Productivity: $Corr\,(alp_t, w_t)$	+0.08	+0.12	+0.15

Note: All columns report changes in moments of HP-filtered variables between pre and post-1984 periods for alternative values of ϕ, denoting the degree of increasing marginal disutility from exerting more effort. All other parameters in the model are fixed at the calibration values used in column (4) of Table 4.3, which corresponds to the total effect of de-unionization.

Table H.3: Robustness to Choice of ψ

Business Cycle Moments	**Changes in Moments due to De-unionization**		
	$\psi = 0.10$	$\psi = 0.25$	Baseline, $\psi = 0.50$
	(1)	(2)	(3)
ALP Correlations			
Output: $Corr\,(y_t, alp_t)$	-0.30	-0.46	-0.58
Employment: $Corr\,(n_t, alp_t)$	-0.19	-0.29	-0.38
Hiring Flows: $Corr\,(h_t, alp_t)$	-0.29	-0.43	-0.50
Volatility of Employment			
Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+19%	+28%	+38%
Conditional $Corr\,(n_t, alp_t)$			
Technology Shock	-0.11	-0.08	-0.07
Demand Shock	-0.20	-0.43	-0.59
Conditional $Corr\,(y_t, alp_t)$			
Technology Shock	-0.02	-0.08	-0.09
Demand Shock	-0.33	-0.69	-0.91
Real Wage Correlations			
Output: $Corr\,(y_t, w_t)$	-0.44	-0.43	-0.41
Employment: $Corr\,(n_t, w_t)$	-0.53	-0.51	-0.50
Labour Productivity: $Corr\,(alp_t, w_t)$	+0.27	+0.19	+0.12

Note: All columns report changes in moments of HP-filtered variables between pre and post-1984 periods for alternative values of ψ, denoting the additional curvature for effort in the production function. Given $\alpha = 0.33$ in the baseline calibration, $\psi \in (0, 0.50]$ to ensure non-increasing returns to scale under perfect competition among intermediate goods firms. All other parameters in the model are fixed at the calibration values used in column (4) of Table 4.3, which corresponds to the total effect of de-unionization.

Table H.4: Robustness to Changes in Nominal Rigidities

Business Cycle Moments	Data (1)	Changes due to De-unionization Model: Baseline (2)	Changes due to De-unionization Model: Changes in θ_p, θ_w (3)
ALP Correlations			
Output: $Corr\,(y_t, alp_t)$	-0.40	-0.58	-0.87
Employment: $Corr\,(n_t, alp_t)$	-0.51	-0.38	-0.43
Hiring Flows: $Corr\,(h_t, alp_t)$	-0.53	-0.50	-0.33
Volatility of Employment			
Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+46%	+38%	+73%
Conditional $Corr\,(n_t, alp_t)$			
Technology Shock	-0.06	-0.07	-0.11
Demand Shock	-1.24	-0.59	-0.55
Conditional $Corr\,(y_t, alp_t)$			
Technology Shock	+0.19	-0.09	-0.17
Demand Shock	-1.21	-0.91	-0.90
Real Wage Correlations			
Output: $Corr\,(y_t, w_t)$	-0.34	-0.41	-0.20
Employment: $Corr\,(n_t, w_t)$	-0.34	-0.50	-0.20
Labour Productivity: $Corr\,(alp_t, w_t)$	-0.10	+0.12	-0.24

Note: All columns report changes in moments of HP-filtered variables between pre and post-1984 periods for both data and model-simulated series. Column (1) reports the empirically observed changes in the business cycle moments. Column (2) corresponds to $\theta_p = \theta_w = 0.75$ for both periods as in the baseline calibration with no change in price and nominal wage rigidities. Column (3) corresponds to changing θ_p from 0.55 to 0.73, and θ_w from 0.65 to 0.74 between the pre and post-1984 periods, along with the changes in Θ and ξ like in column (4) of Table 4.3.

Table H.5: Robustness to Changes in Taylor Rule Parameters

Business Cycle Moments		**Changes in Moments due to Model**	
	Data	ϕ_y decreases	ϕ_π increases
	(1)	(2)	(3)
ALP Correlations			
Output: $Corr\,(y_t, alp_t)$	-0.40	-0.01	+0.26
Employment: $Corr\,(n_t, alp_t)$	-0.51	+0.03	+0.14
Hiring Flows: $Corr\,(h_t, alp_t)$	-0.53	+0.05	-0.07
Volatility of Employment			
Output: $s.d.\,(n_t)\,/s.d.\,(y_t)$	+46%	-1%	-13%
Conditional $Corr\,(n_t, alp_t)$			
Technology Shock	-0.06	+0.05	+0.02
Demand Shock	-1.24	-0.01	+0.00
Conditional $Corr\,(y_t, alp_t)$			
Technology Shock	+0.19	+0.04	+0.71
Demand Shock	-1.21	-0.01	-0.00
Real Wage Correlations			
Output: $Corr\,(y_t, w_t)$	-0.34	+0.02	+0.02
Employment: $Corr\,(n_t, w_t)$	-0.34	+0.09	-0.09
Labour Productivity: $Corr\,(alp_t, w_t)$	-0.10	-0.08	+0.24

Note: All columns report changes in moments of HP-filtered variables between pre and post-1984 periods for both data and model-simulated series. Column (1) reports the empirically observed changes in the business cycle moments. Column (2) refers to the case when the Taylor rule parameter ϕ_y drops from 0.17 to 0.08, and ϕ_π is held constant at 1.70, same as column (3) in Table 4.4. Column (3) corresponds to the case when the Taylor rule parameter ϕ_π increases from 1.01 to 2.20, and ϕ_y is held constant at 0.17.

I 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.

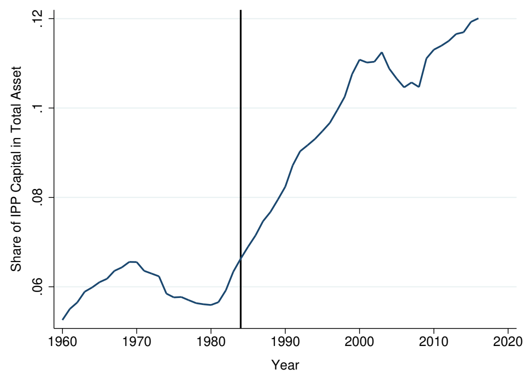


Figure I.1: Share of IPP in Total Non-Residential Capital Stock in the U.S. (1960-2016)

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.

J 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 J.1 and J.2), while that of $\varepsilon_{i,t}$ is the 'Sectoral' variance.

Table J.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 J.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 J.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.