What Explains the Recent Jobless Recoveries?

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Abstract

In this paper I examine how changes between real economic activity and labor market variables can help explain the past three jobless recoveries. In particular, I estimate a correlated unobserved components model for output, sales, employment, and hours per employment, and examine how structural breaks in the relationship between these variables are related to the jobless recoveries.

I find that the Great Moderation coincided with a change in the sensitivity of employment and hours to sales shocks. Most of the changes in the behavior of employment can be attributed to a switch to just-in-time production when it comes to utilizing labor resources. After 1984, employment and hours per employee are much more sensitive to cyclical sales shocks. Meanwhile, there is no evidence of increasing relative importance of permanent fluctuations when it comes to explaining the variance in employment, nor evidence of declining persistence of sales and inventory shocks. Rather than committing to opening full-time positions, firms accommodate temporary increases in demand by temporarily increasing hours, which is consistent with just-in-time employment. These changes help explain the behavior of employment and hours after 1984, including the behavior during the past three recoveries.

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1 Introduction

The past three recessions and their recoveries have been very different from the recessions and recoveries that occurred prior to 1990. For most postwar recoveries prior to 1990, the return of payroll employment to its prerecession levels lagged the GDP turning point by only a few months. The “typical” recovery was characterized by fast job creation that quickly offset the job losses resulting from the recessions. By contrast, the past three recessions and recoveries have been very different with employment growth being sluggish or even negative for many months after the NBER-determined trough. As of May 2012, the US is still in the middle of its third jobless recovery. Because of this slow and very delayed employment growth, many economists refer to the past three recoveries as “jobless”. If there is an explanation for this sluggish employment growth that is common to all three recessions and recoveries, then it might be possible to undertake policies to mitigate the effects of prolonged joblessness.

The main goal of this paper is to examine if there are changes in the relationship between employment, output, sales, and hours that can help explain the change in the behavior of employment. I construct an empirical model that nests the three leading theoretical models that attempt to explain jobless recoveries, and compare the predictions of the empirical model to the predictions of the theoretical models. The main finding of this paper is that there is strong evidence in favor of the just-in-time hypothesis. After the Great Moderation (GM) employment is much more sensitive to shocks in real economic activity, and hours per employee are much more responsive to cyclical fluctuations in hours and sales. It is important to note that the persistence of the sales and inventory shocks has not changed significantly. Most of the changes in the behavior of employment can be explained by changes in the adjustment channels (intensive versus extensive), and these changes do not arise from a change in persistence of sales or other shocks to output. This is consistent with the theory that firms can wait for signs of a robust recovery before they hire new employees, and simply increase the number of hours or utilize more flexible labor resources in the meantime. The results obtained using sectoral data are very similar to the results obtained using aggregate data.

The literature explaining multiple jobless recoveries and examining all three recessions and recoveries is not lengthy. Because these recoveries are so different from the previous recoveries, studying a period that is longer than the trough to peak for a single recovery has been challenging, and most of the literature focuses only on a single trough to peak period. While there is consensus in the literature regarding the stylized facts and the change in the dynamic behavior of employment, there is no consensus on the cause of the jobless recoveries. In the current literature, there are three main hypotheses that are proposed as possible explanations: sectoral reallocation, organizational restructuring, and innovations in labor demand that lead to more flexible hiring practices. Outside the three main strands, productivity-driven changes and compositional changes in labor supply are also frequently used as possible explanations for the jobless recoveries.
The recovery from the 1990 recession was characterized by a very rapid growth in output per hour, leading to the theory that the 1990s were the start of a new era of productivity-led growth. As Gordon (1993) points out, standard macroeconomic models imply that if a recovery is due to very rapid productivity growth, the growth in employment will be slow, but recoveries will be jobless only in the very short run. While high productivity growth certainly accounted for the bounce-back following the recession and for the rapid growth during the 1990s, employment growth following the 2001 recession was dismal for an unusually long period, even though productivity growth was rather robust, implying that standard models that focus on productivity-led growth only cannot completely explain the behavior of employment during the past few years. Furthermore, as of March 2012, there are still widespread concerns about slow productivity growth dragging down employment again, despite the positive growth in employment during the first quarter of 2012, so the slow employment growth during the recovery from the Great Recession cannot be attributed to rapid productivity growth.

The 2001 recovery coincided with a considerable reallocation of jobs across industries, leading to the revived interest in the “Sectoral Shift Hypothesis Theory”. The Sectoral Shift Hypothesis, generally attributed to Lilien (1982) suggests that extensive restructuring can create inefficiencies in the labor market that lead to temporary increase in unemployment. If the slow growth in employment is due to sectoral shifts, demand stimulus would not be efficient in decreasing unemployment, but there may be role for retraining programs and alternative industry-specific policies. Groshen and Potter (2003) use the JOLTS sectoral database to analyze the flow of jobs from industries during the recovery following the 2001 recession, and they argue that most of the slow growth in employment can be attributed to structural changes, in particular to structural changes that are related to sectoral shifts. They look at temporary versus permanent layoffs, interpreting temporary layoffs as the cyclical component of disemployment, and permanent layoffs as the trend component of disemployment. Based on this definition of cyclical employment, they find that most of the new jobs created after the 2001 recession were not due to rehiring workers who were temporarily laid off. They conclude that the slow job creation was due to structural changes, and that sectoral shifts are one of the most plausible explanation for the observed movements in industry-level employment. When looking past the 2001 recovery, the evidence in favor of the sectoral shift hypothesis is mixed. According to the sectoral shift hypothesis, after 1990 there is a marked increase in the importance of permanent shocks and adjustments to permanent shocks when it comes to explaining the dynamics of employment during recessions and the subsequent recoveries.

A third strand of the literature uses the duration of an expansion and the severity of a recession to explain the lag between employment recovery and

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1See, for example, the comments by Christina Romer, Robert Gordon, Ben Bernanke, and Glenn Hubbard for the Wall Street Journal Outlook on Joblessness (Hubbard, John. “Piecing Together the Job-Picture Puzzle” Wall Street Journal on the Web. March 12 2012, accessed March 12 2012
output recovery. Koenders and Rogerson (2005) build a theoretical model in which firms wait to eliminate labor inefficiencies until demand declines, and they postpone hiring during these periods of reorganization. Longer expansions and less mean that there are more accumulated inefficiencies, which leads to a longer recovery lag.

Another strand of the literature that emerged after the 2001 recession ties the jobless recovery to the literature on just-in-time production. The just-in-time hypothesis states that the Great Moderation was linked both to changes in inventory management and to changes in using labor inputs. During the 2001 recovery, permanent job creation was slow, but the number of temporary jobs increased rapidly, as did the number of hours per worker, suggesting that firms switched to using more flexible labor inputs and to just-in-time production not only when it comes to managing inventories, but also when utilizing labor inputs. Extensive summaries of studies that focus on the 2001 recession is provided in Schreft and Singh (2003). In a follow-up paper Hodgson et al. (2005) examine the behavior of hours, overtime, and temporary employment, and conclude that the slow growth of employment during the 2001 recovery can be explained by switching to just-in-time employment. Since firms have access to flexible labor inputs like temporary employees, and are able to increase overtime hours, they can postpone hiring permanent employees until demand is robust enough. Unfortunately, the drawback of these empirical studies is that due to the lack of data on jobless recoveries at that point in time, they also focus on a single peak-to-peak or trough-to-peak period. Two notable exceptions are the work of Engemann and Owyang (2010), and Bachmann (2011). Engemann and Owyang focus on the 1990 and 2001 recoveries, and estimate a univariate smooth transition model for employment growth. Their main finding is that the speed of adjustment of employment has declined significantly after 1982, and that most of the change comes from the manufacturing sector, which is in line with the just-in-time production hypothesis. Bachmann (2011) builds a theoretical model in order to analyze the responses of employment to cyclical movements in output during the 1991 and 2001 recoveries, and he finds that firms have switched towards adjustments on the intensive margin because of the declining persistence of output shocks during the two recessions that preceded the recoveries. Bachmann’s model and its predictions are discussed in detail in Section 3.

The model used in this paper nests the three main competing theories, as I directly estimate and compare if the Great Moderation was accompanied by an increasing importance of permanent movements, a significant decrease in persistence of the sales process, or a significant change in the transmission of output shocks on hours and employment. My approach is somewhat similar in spirit to Gomme’s (2005) probit approach, and to Fabergman (2008) SVAR approach. Fabergman uses an SVAR model with a reallocative and aggregate productivity shock that uses data on output, job creation and job destruction, and Gomme uses a probit model to look at the probability of finding a job and the probability of job separation. In both papers, they find that the Great Moderation coincided with a change in the dynamics of the labor market.
The rest of this paper is organized as follows. Section 2 presents some stylized facts about the dynamics of real macroeconomic aggregates and labor market variables. The theoretical motivation, the empirical model and the estimation procedure are presented in section 3. The results obtained using aggregate data are presented in section 4. Section 4 also presents counterfactual analysis that shows the job losses due to the change in the responsiveness of hours and employment, and separates the variation in employment that was due to permanent shocks from the variation in employment that occurred due to transitory shocks. Section 5 investigates the causes of the changing behavior of employment by comparing the results obtained using aggregate data to the results obtained using disaggregated data, and section 6 concludes.

## 2 Stylized Facts

Table 1 and Figure 1 present some stylized facts about the behavior of macroeconomic aggregates during recoveries before 1984 and after 1984. The table reports the difference between the number of quarters it took for real output, real final sales, payroll employment, aggregate hours (using the updated version of Neville and Ramey’s, 2009, data on aggregate hours), productivity, part-time employment for economic reasons, and overtime hours to reach their pre-recession levels. After 1984, output and sales recover from a recession relatively quickly, returning to the pre-recession level in less than a year, which is comparable to the time it took to return to pre-recession levels before 1984. By contrast, the return of employment and aggregate hours is much slower after 1984. On average, it took 3 quarters for employment and hours to return to their pre-recession levels before 1984, and at least seven quarters to return to the pre-recession levels after 1984.

Table 1: Number of quarters until the pre-recession level is reached (from the GDP trough to old level)

<table>
<thead>
<tr>
<th>Recovery period</th>
<th>GDP</th>
<th>Sales</th>
<th>Emp</th>
<th>H</th>
<th>p</th>
<th>PT</th>
<th>OT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recoveries before 1990</td>
<td>1.33</td>
<td>1.33</td>
<td>3</td>
<td>3.3</td>
<td>1.1</td>
<td>1</td>
<td>3.5</td>
</tr>
<tr>
<td>Recovery from the 1990-91 recession</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td>7</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Recovery from the 2001 recession</td>
<td>1</td>
<td>1</td>
<td>13</td>
<td>7</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Recovery from the 2007-2009 recession</td>
<td>4</td>
<td>4</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>
Figure 1: Payroll employment after the NBER trough (1= Prerecession level). Blue line is the average of recoveries before 1984, the red dashed line is the recovery from the 1990 recession, the green dot-dash line is the recovery from the 2001 recession, and the patterned black line is the recovery from the Great Recession.

What Figure 1 illustrates is difference in the behavior of payroll employment for each of the past three recoveries and for the average of the recoveries prior to 1990 in the three years following the trough. The return to pre-recession level of employment is slow and sluggish in each of the past three recoveries. However, focusing only on the employment levels during a short period of time following a recession may obfuscate the analysis because it may lead to ignoring other important trends (for example demographic trends that affect the employment level in general), and also to ignoring relationships that affect the relationship of employment with other macroeconomic variables over the entire business cycle that may be helpful for explaining the jobless recoveries.
Table 2: Mean growth rates by subsample

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>1948q1-1983q4</th>
<th>1984q1-2012q1</th>
<th>1948q1-1983q4</th>
<th>1984q1-2012q1</th>
<th>1948q1-1983q4</th>
<th>1984q1-2012q1</th>
</tr>
</thead>
<tbody>
<tr>
<td>dy</td>
<td>0.871</td>
<td>0.671</td>
<td>-0.547</td>
<td>1.602</td>
<td>-0.537</td>
<td>0.645</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.129)</td>
<td>(0.642)</td>
<td>(0.951)</td>
<td>(0.813)</td>
<td>(0.987)</td>
<td>(0.645)</td>
<td></td>
</tr>
<tr>
<td>ds</td>
<td>0.868</td>
<td>0.669</td>
<td>-0.121</td>
<td>1.173</td>
<td>-0.296</td>
<td>0.367</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.891)</td>
<td>(0.599)</td>
<td>(0.956)</td>
<td>(0.535)</td>
<td>(0.787)</td>
<td>(0.891)</td>
<td></td>
</tr>
<tr>
<td>demp</td>
<td>0.904</td>
<td>0.325</td>
<td>-0.531</td>
<td>0.701</td>
<td>-0.649</td>
<td>-0.139</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.793)</td>
<td>(0.486)</td>
<td>(0.561)</td>
<td>(0.495)</td>
<td>(0.542)</td>
<td>(0.793)</td>
<td></td>
</tr>
<tr>
<td>dh</td>
<td>0.401</td>
<td>0.292</td>
<td>-1.119</td>
<td>1.015</td>
<td>-0.946</td>
<td>0.064</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.421)</td>
<td>(0.617)</td>
<td>(1.110)</td>
<td>(0.995)</td>
<td>(0.697)</td>
<td>(0.617)</td>
<td></td>
</tr>
<tr>
<td>dh/emp</td>
<td>-0.596</td>
<td>-0.033</td>
<td>-0.668</td>
<td>0.369</td>
<td>-0.297</td>
<td>0.075</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.744)</td>
<td>(0.264)</td>
<td>(0.696)</td>
<td>(0.606)</td>
<td>(0.189)</td>
<td>(0.42)</td>
<td></td>
</tr>
<tr>
<td>dy/h</td>
<td>0.576</td>
<td>0.501</td>
<td>0.099</td>
<td>1.114</td>
<td>0.403</td>
<td>0.971</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.998)</td>
<td>(0.660)</td>
<td>(1.010)</td>
<td>(0.995)</td>
<td>(1.02)</td>
<td>(0.998)</td>
<td></td>
</tr>
</tbody>
</table>

The stylized facts presented in Table 2 illustrate that the jobless recoveries are a phenomenon that is unique to the Great Moderation period. Recoveries before the Great Moderation were characterized by slightly delayed, but rapid growth in employment, and recoveries after 1984 are characterized by much slower employment growth. However, employment is not the only macroeconomic series that exhibits changes in behavior, and these changes are not only restricted to the recovery phase of the business cycle. Recoveries before 1984 were characterized by fast growth in output and sales, a slightly delayed but large growth in employment and hours, and a decline in hours per current employee that was mostly due to the increase in the number of employees. Most of the increase in aggregate hours during the recovery phase came from increases in payroll employment. Furthermore, part-time employment due to economic reasons decreased as employees switched from part-time to full-time employment during a recovery, and the average number of overtime hours per current employees increased only slightly above the mean value. The last two columns of Table 2 illustrate the stark differences between the two subsamples. Both output growth and sales growth were much lower during the past three recoveries than they were during the previous recoveries. After 1984, it took, on average, more than 2 years for aggregate hours to return to their pre-recession levels and employment growth was negative in the year following the trough. It is interesting to note that even though both aggregate hours and employment declined, average hours per current employee grew much faster than the mean, as did overtime hours per current employee.

The first and the third row of Table 2 illustrate that these changes are noticeable not only during the recovery phase, but over the entire business cycle. The stylized facts are consistent with the basic results obtained by Engemann and Owyang (2010): the variance of employment growth has declined, and the difference between the recovery phase and the recession phase/normal phase is smaller. The stylized facts show that the behavior of output, sales, employment, and hours has changed, but the growth rates alone do not explain how the relationship between series has changed, nor do they explain how the dynamics of employment has changed. Since the change in behavior is evident in all series, my goal is to examine if the start of the Great Moderation was not merely the start of a period of lower volatility, but also a time of change in the structural
economic relationship between overall economic activity and employment at the intensive and extensive margins.

3 Model and Estimation

3.1 Theoretical Motivation

The three main hypotheses that attempt to explain jobless recoveries are all closely related to a theoretical models in which firms are allowed to respond to output shocks either by adjusting employment (the extensive margin), or by adjusting hours without adjusting employment (adjusting along the intensive margin, either by increasing hours per employee or by using flexible labor inputs). The just-in-time hypothesis predicts that firms will adjust along the intensive margin because the relative cost of adjusting along the extensive margin has increased, and the relative cost of adjusting along the intensive margin has decreased. The structural reorganization model explains the jobless recoveries by changes in persistence of output shocks. If shocks are less persistent and cyclic movements have became more important relative to permanent movements, then adjustments will occur along the intensive margin. On the other hand, the sectoral shift hypothesis states that after 1990, most of the movements in employment can be explained either by permanent shocks, or by adjustments to those permanent shocks. The model presented below is useful for illustrating the channels through which the pattern of recoveries can change. It is a generalized version of Hansen and Sargent’s (1998) model, and is very closely related to the models used by Bachmann (2011) and by Ramey and Vine (2006).

There is a unit mass of firms, and there is no entry nor exit. Labor services are the only factor of production, and they can be used in an extensive margin (employment) or intensive margin (hours). Firms have the option of employing their workers for $h_1$ straight hours and $h_2$ overtime hours. The total number of workers, $n_1$, works regular hours, and $n_2$ of the workers also work overtime. Firms have a Cobb-Douglas production function to produce a perishable good

$$y = z\omega(n_1^\alpha + n_2^\alpha)$$ (1)

where $z$ and $\omega$ denote aggregate and idiosyncratic productivity levels. The aggregate shock $\log(z)$ evolves according to an AR(1) process, with Gaussian innovations $\nu$ with zero mean and variance $\sigma_{agg}^2$, and the idiosyncratic shocks follow a Markov chain that approximates a continuous AR(1) process with Gaussian innovations. Aggregate and idiosyncratic shocks are independent, as are shocks across firms. The wage bill for each firm is $w_1h_1n_1 + w_2h_2n_2$, where $w_1$ is the regular wage and $w_2$ is the overtime wage. Choosing $n_1$ and $n_2$ is equivalent to choosing the total employment and average hours per worker. Firms face adjustment costs to adjust their employment stock, but no adjustment costs to adjust hours. Under no employment adjustment

$$y^{na}(\omega, n_1^-, z) = z\omega(n_1^-(1 - q))^\alpha + h_2(n_2^-(n_1^-))^\alpha)$$ (2)
where \( n^*_2 \) is the optimal choice of overtime employment. Adjustment costs paid conditional on adjusting employment, \( n_1 \) are given by

\[
AC(\omega, n^*_1, \xi, z) = [1 - \theta + \theta y^{na}(\omega, n^*_1, z)]\xi
\]

(3)

where \( \xi \) is a stochastic adjustment cost factor, drawn from a uniform distribution \( G(\xi) = U([0, \bar{\xi}]) \) that is time-invariant, and draws are independent across time and establishments.

There is a continuum of identical households and profits, \( \Pi \), are distributed evenly across households. Each member of a household is endowed with one unit of time, and has the following felicity function

\[
u(c, h) = \log(c - Ah^1 - \sigma h^1 - \sigma h^2) \]

(4)

where \( \sigma_h \leq 0 \) is the curvature parameters, and \( A \geq 0 \) is constant. The household chooses the fraction of its members that consume leisure and commodity consumption by maximizing the household utility function:

\[
U(c_0, c_1, c_2, \check{n}_1, \check{n}_2) = (1 - \check{n}_1)\log(c_0) + (\check{n}_1 - \check{n}_2)\log(c_1 - A\frac{h^1}{1 - \sigma_h}) + \check{n}_2\log(c_2 - A\frac{h^2}{1 - \sigma_h})
\]

(5)

subject to the budget constraint:

\[
\Pi + w_1 h_1 \check{n}_1 + w_2 h_2 \check{n}_2 = (1 - \check{n}_1) c_0 + (\check{n}_1 - \check{n}_2) c_1 + \check{n}_2 c_2,
\]

where the indices refer to the fraction of the household members that does not work, the fraction that works regular hours, and the fraction that works regular and overtime hours.

The firm’s dynamic programming problem is given by:

\[
V_{t+1}(\omega, n, \xi, z, \mu) = \max \{ \max_{\check{n}_1, \check{n}_2} \left[ \omega c_1((n_1(1-q))^\alpha + h_2 n_2^\alpha) - w_1(z, \mu) h_1 n_1(1-q) - w_2(z, \mu) h_2 n_2 \right] p(z, \mu) + \beta EV_t(\omega', n_1(1-q), z', \mu'), \right. \\
-AC(\omega, n^*_1, \xi, z) p(z, \mu) + \max_{n^*_1} \left[ \omega c_1((n'_1(1-q))^\alpha + h_2 n_2^\alpha) - w_1(z, \mu) h_1 n'_1(1-q) - w_2(z, \mu) h_2 n_2 \right] p(z, \mu) + \beta EV_t(\omega', n'_1, z', \mu') \}
\]

(6)

where \( \mu \) is the joint distribution of \( \omega \) and \( n^*_1 \), \( p() \) is the marginal utility of consumption, and both expectation operators average over next period’s realizations of the aggregate and idiosyncratic shocks conditional on this period’s values.

The first order conditions for the households are
\[ c_0 = c_1 - A \frac{h_1^{1-\sigma_h}}{1-\sigma_h} = c_2 - A \frac{(h_1 + h_2)^{1-\sigma_h}}{1-\sigma_h} \]  
(7)

\[ w_1 h_1 = A \frac{h_1^{1-\sigma_h}}{1-\sigma_h} \text{ and } w_2 h_2 = A \frac{(h_1 + h_2)^{1-\sigma_h} - h_1^{1-\sigma_h}}{1-\sigma_h} \]  
(8)

\[ p = (\Pi + w_1 h_1 \bar{n}_1 + w_2 h_2 \bar{n}_2 - (\bar{n}_1' - \bar{n}_2') A \frac{h_1^{1-\sigma_h}}{1-\sigma_h} - \bar{n}_2' A \frac{(h_1 + h_2)^{1-\sigma_h}}{1-\sigma_h})^{-1}, \]  
(9)

where a bar above a value denotes an average value over households.

The recursive equilibrium is characterized by

1. firm optimization (given wages and prices, firms solve (6))
2. household optimality (given wages and prices, firms choose labor supply in accordance with the first-order conditions that maximize (5))
3. the commodity market clears
4. the labor market clears
5. The evolution of \( \mu, \mu' = \Gamma(z, \mu) \) is induced by the firm and household choices and the exogenous process for \( z \) and \( \omega \).

The model does not have an analytical solution, and it has to be solved by approximating the distributions using numerical simulations. The details of the algorithm when there are no changes in the structural parameters over time can be found in Bachmann (2011).

The key qualitative result is that in this framework, changes in employment dynamics can occur through three channels. They can occur because of changes in the persistence of aggregate or idiosyncratic shocks, through changes in the relative importance of permanent shocks, or through changes in the adjustment costs. Cyclical shocks are absorbed through the intensive margin, and permanent shocks are absorbed through the extensive margin. Another key implication higher adjustment costs mean that firms will delay increasing employment following a recession, leading to a jobless recovery. Bachmann calibrates the model to match US data, assuming no changes in adjustment costs, and concludes that when the model is calibrated to match U.S. aggregate data, a significant part of the movements in employment during the jobless recoveries can be attributed to less persistent cyclical movements in output. Ramey and Vine (2006) calibrate a similar model to match U.S. automotive data. They simulate the responses of hours and employment, and they also find that cyclical movements are absorbed through the intensive margin, and conclude that movements in production and sales have become both less persistent and smaller in magnitude after 1984. The decreasing persistence of shocks and the smaller cyclical movements during recessions is at odds with empirical findings from univariate models of output.
(see, for example, Sinclair, 2010, or Morley and Piger, 2012), where most of the movements during recessions are caused by large transitory fluctuations.

Neither Bachmann nor Ramey and Vine allow for the possibility that there was a change in the adjustment costs of employment, which is the crux of the just-in-time hypothesis. Ideally, one would solve the theoretical DSGE model allowing for a break in the cost of adjusting employment and for movements in the cyclical component of employment that can be explained by adjustments to permanent movements in output, thus building a model that nests all three main hypotheses\(^3\). Unfortunately, as discussed both in Bachmann (2011), and in Ramey and Vine (2011), full structural analysis is quite computationally burdensome in this case, even for the model that does not assume any breaks in the parameters. Instead, I build an empirical model that nests the three competing hypotheses, in which the reduced-form parameters are closely related to the parameters from the structural model.

### 3.2 Empirical Model

As discussed in the previous subsection, in this paper build a formal multivariate econometric model that implicitly nests the three competing theories (increasing importance of permanent movements, just-in-time production, and structural reorganization). In a related model used to investigate the role of inventories in the Great Moderation, Morley and Singh (2011), find that the relationship between inventories and sales (and thus between output and sales) changed after 1984. In this paper I adapt their approach and examine if there are similar changes in the relationship between output, sales, and labor market variables before and after 1984. Mirroring the theoretical setup, firms can respond to output shocks by adjusting employment, and by adjusting hours per current employee.

The empirical model is given by the following equations

\[
y_t = \tau_t + c_y \\
s_t = \tau_t + c_s \\
e_t = \zeta_t + c_e \\
h_t = \mu h_t + c_h
\]

where \(y_t\) is hundred times the logarithm of real GDP, \(s_t\) is hundred times the logarithm of real final sales, \(e_t\) is the logarithm of employment, and \(h_t\) is

\(^3\)The just-in-time hypothesis corresponds to changes in the adjustment parameters, the structural reorganization hypothesis corresponds to lower persistence and amplitude of cyclical movements, especially during recessions, and the sectoral shift hypothesis corresponds to increasing importance of adjustments to permanent movements.
the logarithm of aggregate hours per employee. Output and sales have the same stochastic trend

\[ \tau_t = \mu_1 + \tau_{t-1} + \eta_t, \quad (14) \]
reflecting the fact that output and sales are cointegrated, as discussed in detail below.

The stochastic trend in employment is the sum of two components: \( \tau_t \) and \( \kappa_t \), where

\[ \zeta_t = \tau_t + \kappa_t \quad (15) \]

and

\[ \kappa_t = \mu_2 + \kappa_{t-1} + \nu_t. \quad (16) \]

The cyclical components are assumed to be stationary, and their dynamics can be described by the following equations:

\[ \Phi_1(L)(y_t - \tau_t - \mu_{yt}) = \lambda_{yt}\eta_t + \lambda_{ys}\epsilon_s + \epsilon_y. \quad (17) \]
\[ \Phi_2(L)(s_t - \tau_t - \mu_{st}) = \lambda_{st}\eta_t + \epsilon_s \quad (18) \]
\[ \Phi_3(L)(e_t - \tau_t - \kappa_t - \mu_{et}) = \lambda_{et}\eta_t + \lambda_{ey}\epsilon_y + \lambda_{es}\epsilon_s + \epsilon_e \quad (19) \]
\[ \Phi_4(L)(h_t - \mu_{ht}) = \lambda_{ht}\eta_t + \lambda_{hy}\epsilon_y + \lambda_{hs}\epsilon_s + \lambda_{he}\epsilon_e + \epsilon_h \quad (20) \]

The first stochastic component, \( \tau_t \), can be interpreted as the productivity trend that affects long run output and therefore it affects long run employment. The second trend component reflects demographic, preference, and exogenous shocks to the labor share that do not affect the cyclical components of output, sales, hours, or employment directly. This specification is motivated by the results of Neville and Ramey (2009) and Kahn and Rich (2009), who show that low-frequency movements in hours and employment can be explained by two separate factors - productivity and demand shocks and demographic or taste shifts that are not perfectly correlated with productivity shocks. The shock \( \nu \) can also be interpreted as a preference shift as in Rios-Rull and Santaulalia-Llopis (2010), which is also consistent with Francis and Ramey’s model. The demographic or preference shocks are allowed to be correlated with shocks to the productivity trend, but they do not affect the cyclical components of any of the series directly within a period. Not restricting the correlation between the two trends to be zero allows demographic changes like aging population or changes in the labor force to affect output and productivity in the long run, but they have negligible impact on the cyclical components within a quarter\(^4\).

\(^4\)The non-zero correlation is meant to capture two facts. First, permanent shocks that increase productivity mean that less employees are needed to produce a unit of output. Second,
Equations (13) and (20) describe the behavior of hours per employee. By focusing on hours per employee, I am able to abstract from the influence of demographic changes on hours within a quarter. This specification also has the advantage that it directly disentangles the response of aggregate hours into the response of employment and the response of hours per employee, thus allowing me to compare the different hypotheses about the behavior of employment directly. The hours per employee series appears to be stationary, which can be easily confirmed by stationarity or unit root tests. In section 4.4, I allow for a stochastic trend in the hours per employee series (which accounts for a drift in the mean), but the results are virtually identical to the results obtained assuming that hours per employee are stationary. Figure 3 below illustrates the motivation for modeling output and sales as cointegrated series. Both output and sales are nonstationary, which can be easily confirmed by pre-testing using standard unit root or stationarity tests, but the first differences and the series \( d = y - s \) are stationary. Indeed, as shown in Table 3, I reject the null of no cointegration if I assume that the cointegrating vector is \([1 - 1]\). Estimating the cointegrating vector leads to estimates that are very close to \([1 - 1]\), and again I reject the null of no cointegration, implying that output and sales share the same stochastic trend.

\[ d = y - s \]

Figure 2: The left panel plots real GDP and real final sales (both series are 100 times the natural logarithm). The first differences of both series and the series \( d = y - s \) are plotted in the right panel. The sample size is 1948q1-2011Q4. Output and its first differences are plotted in blue, sales is the red solid line, and \( d \) is the patterned black line.

Productivity shocks that lead to higher income may lead to preference shifts or to simply enjoying more leisure time, if income is sufficiently high. Based on these interpretations, one would expect the correlation between the two permanent shocks to be negative, but I do not restrict it to be less than zero.

If looking at \( y \) and \( s \) in levels, the series \( y - s \) is equal to change in inventories (by definition). Since the model here uses log levels, the difference \( d \) can be interpreted as a close proxy for the change in inventories.
The polynomials \( \Phi^{-1}(L) \) capture the autoregressive dynamics of the transitory components. The shocks \( [\eta \nu \epsilon_y \epsilon_s \epsilon_e \epsilon_y] \) are the structural shocks that drive the model, and the impact coefficients \( \lambda_{ij} \) that describe the response to those shocks. The AR coefficients are directly related to the persistence of the transitory movements in the series, and the impact coefficients are related to the sensitivity of the transitory components to structural shocks. In particular, the impact coefficients on employment and hours per employee can directly be interpreted as adjustment coefficients.

The output shocks \( \eta \) and the preference/demographic shocks \( \nu \) are allowed to be correlated within a period, but to ensure identification, the correlation is restricted to be less than 1 in absolute value and they are assumed to be uncorrelated to the structural transitory shocks. The structural transitory shocks are uncorrelated to each other within a period. Allowing the permanent shocks \( \eta \) and \( \nu \) to be correlated allows for technological change to lead to demographic and preference changes, and vice versa, but by restricting the correlation to be less than perfect, the shocks can be identified separately. In order to identify the impact coefficients, I assume that firms take sales as exogenous within a period, and the only shocks that affect transitory sales are permanent output shocks and transitory sales shocks. This identification scheme mirrors the usual VECM timing assumption that production is set based on expected sales. The transitory component of output is affected by the permanent shocks to output, the transitory sales shock, and an independent structural shock that can be interpreted as an inventory mistake shock. The transitory component of employment is affected by permanent shocks and by transitory shocks to sales, inventories, and by idiosyncratic employment shocks. Within a period, hours are affected by permanent shocks to output, by transitory sales, inventory, and employment shocks, and by their own transitory shocks. The impact coefficients \( \lambda_{ij} \) capture the response of the observed variables to the uncorrelated structural shocks. By using impact coefficients I allow the permanent and the transitory movements to be correlated, while keeping the structural shocks uncorrelated. The impact coefficients play two important roles in this framework. First, they obviously determine the scale of the responses to a unit shock. Second, they provide a way to orthogonalize the shocks that does not depend on restricting the responses of the cyclical components beyond the exogeneity restrictions implied by equations 8 through 10. The orthogonalization scheme used here nests the orthogonalization scheme used in the VAR models that study the response of hours to technology shocks (see, for example, Gali, 1999, Basistha, 2009, or Rios-Rull et al., 2011), without imposing sign restrictions on the responses of hours and employment. Using a UC model is a relatively “agnostic” way to cir-
cumvent the problem of defining trend and cycle employment, because it does
not entail making the common assumption that all permanent layoffs are due
to structural changes and are made with no intention of ever rehiring workers
to fill that position again.

The autoregressive polynomials $\Phi_i(L) = 1 - \phi_1 L - \ldots - \phi_{i,p_i} L^{p_i}$ are assumed
to have roots strictly outside the unit circle for $i = y, s, emp, h$. As discussed in
Morley et al. (2003), an unobserved components model with correlated shocks is
identified given sufficiently rich dynamics. To ensure identification in this model
$p_i$ has to be greater than 1 for each $i = 1, 2, 3, 4$. Following most of the UC
literature, I set $p_i = 2$ for $i = 1, 2, 3, 4$. The structural shocks are assumed to be
Gaussian. If the cyclical components are symmetric, as is commonly assumed
in DSGE models, then $\mu_{it} = 0$ for all $i, t$ and the model given by equations
(10)–(20) is identical to a restricted four-variate unobserved components similar
to the the unrestricted models used by Sinclair (2009) and Basistha (2009). 6

It is well-known that there was a general decline in volatility in real macroeco-
nomic variables around 1984, and this decline in volatility has been well docu-
mented in the literature (see, for example Kim and Nelson (1999), or McConnel
and Perez-Quiros (2000)), and there is a general consensus that the break in
variance occurred between 1983 and 1985. Since the timing of the Great Mod-
eration is not the primary focus of this paper at this point, I take the timing
of the break as exogenous. Engemann and Owyang's (2010) estimated break
dates for the univariate employment model are also close to the estimated break
dates for the start of the Great Moderation, implying that treating the break as
exogenous is a plausible assumption. It is, however, important to note that I do
not impose the restriction that the ratios of variances of the structural shocks
remain the same, nor the restriction that the impact coefficients remain con-
stant (ie that the correlation between the trend and the cycle does not change
over time) that is common in the UC literature. Not imposing this restriction
allows the correlation between the variables to change across subsamples, thus
allowing for a change in the transmission mechanism between sales and output
that is due to a change in the correlation of shocks.

To distinguish between the competing theories, I focus on three key questions

1. Can the different responses of employment to output shocks be explained
   by the change in the sensitivity of employment and hours in overall eco-
   nomic activity?

2. Are there significant changes in the persistence of transitory movements
   in sales and output?

3. How much of the relative fluctuations in employment can be explained by
   permanent shocks, and how much can be explained by transitory shocks?

6In particular, it is equivalent to a model where the correlation between employment trend
and the cyclical components of all variables can be expressed as functions of the correla-
tions between the output trend and the cyclical components and the correlations between
the cyclical components.
In order to analyze these issues, I estimate the baseline model separately for the pre-Great Moderation period (1948q1-1983q4) and for the post-Great Moderation Period (1984Q1-2011q4), allowing both the autoregressive polynomials $\Phi_i(L)$ and the variance-covariance matrix to change. This procedure allows me to directly examine if the Great Moderation was a time of change not only for inventory management practices, but also for labor management and utilization. Rather than using temporary layoffs as a measure of cyclical (dis)employment, I use an unobserved components (UC) model to separate the employment trend from the employment cycle. An advantage of the UC model is that it does not require imposing long-run restrictions to identify the output trend, and it allows me to disentangle the trend from the cycle component while still permitting cyclical movements to be driven by adjustments to permanent shocks.

3.3 Estimation

The linear UC model that restricts $\mu_{it} = 0$ has 28 parameters for each subsample, and it is identical to a reduced-form vector error correction model that has both a VAR and a vector MA component. The nonlinear models have 32 and 36 parameters. Given the fact that even the restricted model is parameter-rich, and the fact that VECM and VARMA models can be difficult to estimate using maximum likelihood because of weak identification, the model is estimated using Bayesian methods. In particular, I use a multi-block random walk chain with a Student-t proposal version of the Metropolis-Hastings (MH) algorithm. As pointed out by Morley and Singh (2011), there are two main advantages of using Bayesian estimation over maximum likelihood estimation in unobserved components models. First, the Bayesian approach allows me to directly capture the uncertainty about the parameters when constructing the impulse responses and when performing counterfactual analysis. Second, previous research that uses UC models to decompose macroeconomic variables frequently finds that the estimated parameters for many US macroeconomic series are close to the boundary of the parameter space (see, for example, Sinclair (2009), who uses a bivariate model for unemployment and output and finds correlations that are very close to -1, or Basistha (2009), who uses a four-variate model for productivity, inflation, output per capita, and hours per capita and finds that some of the trend variances are close to 0), there is a reason to suspect that some of the implied correlations and the variance of the trend in hours per capita may be close to the boundary of parameter space. Using Bayesian methods allows me to find an interior mode of the posterior even with non-informative priors, thus circumventing the pile-up problem.

The parameters were estimated by casting the model into state-space form, and updating each parameter at each MH draw. The state-space representation for the UC model is given in Appendix 1, and a detailed description of the sampler and the priors is provided in Appendix 2.
4 Estimation Results

4.1 Parameter Estimates

As discussed in Sections 1 and 2, the data series used are quarterly US real GDP and real final sales from BEA, total non-farm payroll employment (converted to quarterly frequency using arithmetic averages), and Francis and Ramey’s updated measure of aggregate hours. The first subsample covers the period 1948q1-1983q4, and the second subsample covers the period 1984q1-2011q4. All series are converted to hundred times the natural logarithm of the raw data series. Estimating the model given by equations 10-20 for each subsample allows me to account for three types of structural changes: changes in the volatility of the structural shocks, changes in the autoregressive parameters, and changes in the impact coefficients. Since the responses of hours and employment are non-linear functions of the parameters, simply looking at changes in the structural parameters without looking at how the shocks are transmitted over time is not very informative, but large changes in the impact parameters combined with a change in relative volatilities can shed light on the sources of the change in the behavior of employment. If the changes occurred due to just-in-time employment practices or due to similar structural changes in the labor market, one would expect both the ratio $\lambda_{es}/\lambda_{ey}$ and impact coefficients on hours per capita to increase significantly. As discussed in detail below, this is indeed the case.

Tables 4 and 5 present the median estimates and the standard deviations for the autoregressive coefficients and for the volatility and the impact coefficients. The autoregressive coefficients (and thus the persistence of the cyclical components) are very similar across subsamples. The employment trend is very persistent in both subsamples, and the cyclical component of employment is large and volatile. The volatility of employment declines during the great moderation (consistent with the findings in Owyang et al., 2008), but the relative ratio of the implied trend component vs the volatility of the cycle component actually declines. It is important to note that the implied correlation between the trend component shocks to the aggregate trend in employment $\tau^1_t$ and $\omega_e$ is close to $-1$ (the median estimates, expressed as a function of the impact coefficients and the structural variances, were -0.881 and -0.912) in both subsamples. This means that a lot of the cyclical movement in employment does come from adjustments to permanent shocks, but the relative importance of those permanent shocks has not increased after 1984.

The estimated volatilities of both the permanent shocks to output and the cyclical components of output and sales are lower for the second subsample, which is not surprising, because the break is chosen to coincide with the start of the Great Moderation. A particularly important result in this framework is not the decline in volatility, but the decline in the ratio of the volatility of the output relative to the volatility of sales. Before the start of the Great Moderation, the median estimate for the ratio of the volatility of the cyclical structural shocks of output to the volatility of the cyclical structural shocks to sales was 1.289. After 1984, the ratio drops to 0.98. Together with the change in the impact
coefficients on sales, the change in this ratio explains a lot of the observed behavior in employment after 1984, as shown in the next two subsections. It is interesting to note that the median estimate for the volatility of hours per capita does decrease, but the decrease is not significant.

The impact coefficients for the permanent output shock do not change drastically after the break. It is, however, important to note that the impact coefficients of for the permanent shock $\eta$ on employment and hours are negative. Contrary to predictions from RBC models (see, for example, Rios-Rull et al., 2011), permanent shocks to productivity have a transitory negative impact on hours and employment. These estimates imply that hours and employment do not adjust to steady-state immediately following a permanent shock. The median estimated impact coefficient $\lambda_{e\eta}$ is -0.699 for the first subsample and -0.722 for the second subsample, and both of those parameters are significantly smaller from zero. The median estimated impact coefficient $\lambda_{h\eta}$ is -0.184 for the first subsample, and -0.252 for the second subsample, and again the credibility intervals for both estimates do not cover zero, even when using conservative 95% CIs. Even though I use different measure of hours and productivity, the implied correlations between the shocks $\eta$ and $u_h$ are also close to the parameter estimates obtained by Basistha (2009), who looks at the correlations between productivity, hours per capita, and inflation. The negative impact coefficients are at odds with RBC predictions, but they are consistent with Gali's (1999) New-Keynesian DSGE model where productivity shocks have temporary negative effect on hours. The impact coefficients $\lambda_{e\eta}$ and $\lambda_{h\eta}$ and the correlation between the productivity shocks and the demographic shocks do not change significantly across subsamples, implying that there is no evidence that permanent technology shocks have became more important in explaining movements in employment after 1984.

The largest change occurred in the impact coefficients for the transitory inventory and sales shocks on the employment and hours cycles. The median estimate for the impact coefficient of sales on employment, $\lambda_{e\eta}$, was 0.153 before 1984, and 0.658 after 1984. Before the Great Moderation, a positive sales shock increases log employment by 0.15, and after 1984, a positive cyclical sales shocks increases employment by 0.65, which is more than four times the pre-GM value. The median estimate for the impact of inventory shocks on employment changes from 0.730 to 0.231. If one only looks at the impact coefficients, these results imply that within a quarter, the effect of a positive structural inventory shock equal to 1 on employment has gone down by 60%, and the effects of a positive structural shock to sales on employment has gone up by nearly 421%. The change in the impact coefficients of sales and non-sales output shocks on hours per employee is just as striking. Before the Great Moderation, hours per employee responded positively to inventory shocks within a quarter, but the response was small (the median estimate was 0.09, with standard deviation of 0.01). After 1984, the impact coefficient increases to 0.223, meaning that the response of hours to non-sales shocks on impact has gone up by 240%. The increase in the impact coefficients of sales on hours is also significant, but not as large as the increase in the impact coefficients on employment. The median
estimate of $\lambda_{hs}$ goes from 0.141 to 0.218, but both estimates have large standard deviations. It is interesting to note that the median and the distribution of the impact response of hours per capita to the permanent shocks $\eta$ and to the inventory shocks $\epsilon_y$ are similar to those obtained by Gali and Rabanal (2005), even though they use a different specification for hours per capita, and a different orthogonalization scheme.

The changes in the relative ratios of the variances and the impact coefficients are consistent with the switch to just-in-time employment hypothesis that pos- tulates that if firms are using more flexible labor inputs, hours and aggregate hours would increase much more after the break, and that the response of employment to sales should increase after the break.

The unobserved components model allows the structural shocks to affect the path of output, sales, employment, and hours in two ways. First, the shocks affect the variables through the impact coefficients, and then they affect the variables through the autoregressive coefficients. Since the shocks propagate through both channels, a small change in the AR coefficients and in the impact coefficients may potentially lead to a large change in the response of employment, and a change in the impact coefficients may be amplified or dampened over time through the AR coefficients. Comparing both the the contribution of each type of shock to the variance in employment is a useful starting point for evaluating the importance of the changes in the propagation mechanism versus the changes in the impact coefficients. If one were to look at impulse responses, due to the nature of the model, the responses of the cyclical component of employment and hours to a structural cyclical sales and inventory shocks will have the same shape as the responses to the permanent shock, but they will be rescaled by $\lambda_{ey}, \lambda_{es}, \lambda_{hy},$ or $\lambda_{hs}$. Nevertheless, comparing the scaled response functions is quite revealing because it illustrates by how much the impact of a sales shock has changed relative to a non-sales shock. From the values in Tables 4 and 5, it is straightforward to calculate that before the Great Moderation, the response of employment to a unit inventory/non-sales shock was 4.86 times larger than the response to a unit sales shock. After the break, the response to a unit inventory shock is 35% of the response to a unit sales shock. When considering “typical” shocks equal to 1 standard deviation, the response of employment to inventory shock relative to the response to sales shock was equal to 6.271 before the break, and to 0.37 after the break. The median ratio of the response of hours to an inventory shock compared to the response of hours to a sales shock went from 0.832 to 0.879, which is not nearly as drastic as the change in the ratio of employment responses. These numbers illustrate three important points. First, as shown in Table 4, there is no significant change in the transmission of employment shocks, or of hours shocks. Second, the change in the impact coefficient of sales on employment matters, even when one only looks at unit shocks. Within a period, a unit shock will have effects that are more than 400% larger. Third, the change in the relative volatility of output to sales matters.

The graphs that compare the impulse responses over subsamples are available from the author upon request.
Before 1984, the volatility of output was much larger than the volatility of sales, and inventory shocks had larger impact coefficient on employment than sales shocks. After the start of the Great Moderation, the relative volatility of output to sales has declined, and the impact coefficient of non-sales shocks is smaller. These results are consistent with a switch to just-in-time production, as discussed in the previous subsection. The ratios of the impulse response functions clearly show that the responses of employment to sales and inventory shocks have changed, but they only focus on the behavior of employment to one-time shocks. In order to further disentangle how much of the movement in employment and hours can be attributed to the permanent shocks, and how the change in the impact coefficients affected the path of the employment, I perform counterfactual simulations that allow me to address those questions directly.
Table 4: Autoregressive and Mean Coefficients

<table>
<thead>
<tr>
<th></th>
<th>1948q1-1983q4</th>
<th>1984q1-2011q4</th>
<th>1984q1-2007q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_1$</td>
<td>0.856 (0.071)</td>
<td>0.508 (0.054)</td>
<td>0.623 (0.074)</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>-0.437 (0.015)</td>
<td>-0.287 (0.014)</td>
<td>-0.244 (0.112)</td>
</tr>
<tr>
<td>$\phi_{11}$</td>
<td>1.276 (0.127)</td>
<td>1.341 (0.158)</td>
<td>1.113 (0.111)</td>
</tr>
<tr>
<td>$\phi_{12}$</td>
<td>-0.650 (0.103)</td>
<td>-0.737 (0.100)</td>
<td>-0.474 (0.053)</td>
</tr>
<tr>
<td>$\phi_{21}$</td>
<td>0.508 (0.090)</td>
<td>0.590 (0.064)</td>
<td>0.717 (0.100)</td>
</tr>
<tr>
<td>$\phi_{22}$</td>
<td>0.186 (0.101)</td>
<td>-0.011 (0.051)</td>
<td>0.080 (0.031)</td>
</tr>
<tr>
<td>$\phi_{31}$</td>
<td>1.486 (0.102)</td>
<td>1.007 (0.131)</td>
<td>1.11 (0.169)</td>
</tr>
<tr>
<td>$\phi_{32}$</td>
<td>-0.548 (0.093)</td>
<td>-0.088 (0.09)</td>
<td>-0.19 (0.100)</td>
</tr>
<tr>
<td>$\phi_{41}$</td>
<td>1.396 (0.074)</td>
<td>1.485 (0.091)</td>
<td>1.732 (0.122)</td>
</tr>
<tr>
<td>$\phi_{42}$</td>
<td>-0.543 (0.081)</td>
<td>-0.594 (0.085)</td>
<td>-0.910 (0.210)</td>
</tr>
</tbody>
</table>

Table 5: Volatility and Impact Coefficients

<table>
<thead>
<tr>
<th></th>
<th>1948q1-1983q4</th>
<th>1984q1-2011q4</th>
<th>1984q1-2007q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_\eta$</td>
<td>1.369 (0.301)</td>
<td>1.007 (0.021)</td>
<td>0.936 (0.112)</td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td>1.141 (0.157)</td>
<td>0.689 (0.102)</td>
<td>0.737 (0.154)</td>
</tr>
<tr>
<td>$\sigma_y$</td>
<td>0.891 (0.041)</td>
<td>0.282 (0.029)</td>
<td>0.147 (0.052)</td>
</tr>
<tr>
<td>$\sigma_s$</td>
<td>0.691 (0.101)</td>
<td>0.287 (0.080)</td>
<td>0.189 (0.032)</td>
</tr>
<tr>
<td>$\sigma_e$</td>
<td>1.010 (0.142)</td>
<td>0.916 (0.095)</td>
<td>0.951 (0.102)</td>
</tr>
<tr>
<td>$\sigma_h$</td>
<td>0.775 (0.112)</td>
<td>0.599 (0.144)</td>
<td>0.555 (0.100)</td>
</tr>
<tr>
<td>$\rho_{\eta v}$</td>
<td>-0.706 (0.110)</td>
<td>-0.792 (0.222)</td>
<td>-0.786 (0.241)</td>
</tr>
<tr>
<td>$\lambda_{\eta y}$</td>
<td>-0.941 (0.110)</td>
<td>-0.748 (0.051)</td>
<td>-0.806 (0.111)</td>
</tr>
<tr>
<td>$\lambda_{\eta s}$</td>
<td>-0.771 (0.075)</td>
<td>-0.693 (0.122)</td>
<td>-0.800 (0.060)</td>
</tr>
<tr>
<td>$\lambda_{\eta e}$</td>
<td>-0.699 (0.051)</td>
<td>-0.722 (0.214)</td>
<td>-0.618 (0.102)</td>
</tr>
<tr>
<td>$\lambda_{\eta h}$</td>
<td>-0.184 (0.002)</td>
<td>-0.252 (0.011)</td>
<td>-0.294 (0.042)</td>
</tr>
<tr>
<td>$\lambda_{ys}$</td>
<td>0.531 (0.127)</td>
<td>0.632 (0.098)</td>
<td>0.645 (0.152)</td>
</tr>
<tr>
<td>$\lambda_{sa}$</td>
<td>0.15 (0.031)</td>
<td>0.658 (0.190)</td>
<td>0.783 (0.114)</td>
</tr>
<tr>
<td>$\lambda_{se}$</td>
<td>0.141 (0.111)</td>
<td>0.218 (0.072)</td>
<td>0.222 (0.054)</td>
</tr>
<tr>
<td>$\lambda_{sy}$</td>
<td>0.730 (0.022)</td>
<td>0.231 (0.161)</td>
<td>0.211 (0.052)</td>
</tr>
<tr>
<td>$\lambda_{hs}$</td>
<td>0.091 (0.010)</td>
<td>0.223 (0.012)</td>
<td>0.245 (0.091)</td>
</tr>
<tr>
<td>$\lambda_{he}$</td>
<td>0.230 (0.311)</td>
<td>-0.016 (0.121)</td>
<td>-0.033 (0.055)</td>
</tr>
</tbody>
</table>

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4.1.1 Do Cyclical Shocks Matter?

The first set of counterfactuals tackles the second set of key question: how much of the movement in employment and hours can be explained by permanent movements, and do cyclical movements matter after 1984? In order to answer those questions, I set up a counterfactual experiment that is akin to the hours-decomposition by Gali and Rabanal (2005), and to the variance decomposition counterfactual VAR experiments for the response of aggregate hours by Santaeulalia-Llopis (2012). The goal of this experiment is to examine how much of the movement in employment can be attributed to each structural shock. The set up is straightforward: given the observed shocks, I simulate the path of employment for the case when only permanent shocks affect the system, and for the case when only one of the structural cyclical shocks affects the system. To account for parameter uncertainty, at each iteration of the MH sampler after the burn-in I feed the observed shocks for the given parameter draw through the system using the first two quarters of 1984 as the initial values. Figure 6 below plots the posterior mode for the simulated series. Since the shocks $\eta$ and $\nu$ are correlated, they are fed through the system jointly. This decomposition of the path of employment is different from the standard trend-cycle decomposition in UC models because the movements due to the permanent shocks account for movements in the stochastic trend and for movements in the cyclical component that are caused by permanent shocks.

As shown in the first panel of Figure 3, a lot of the movements in employment can be explained by permanent shocks and adjustments to permanent shocks, but the movements that are caused by cyclical fluctuations are also quite volatile, and they match up the NBER recessions and the period following the recession quite well. The recessions and the jobless recovery periods in this model cannot be solely attributed to permanent shocks or adjustments to those shocks only. On the contrary, a lot of the movement in employment during recessions and recoveries comes from large transitory movements. This is in line with the findings of Morley and Piger (2012) and Sinclair (2010). The fact that sales shocks drive a lot of the movements in employment is consistent with the just-in-time theory. The decomposition of the hours per employee series is also consistent with this assumption. As shown in Figure 4, hours per capita are procyclical, but quite volatile. A lot of the fluctuations do come from responses to the permanent shocks, but the cyclical shocks are not negligible, especially during recessions and recoveries.
Figure 3: The graph plots the decomposition of the path of employment. The left panel plots the observed path of log employment (solid blue line), the posterior mode of the path of employment caused by permanent shocks and adjustments to permanent shocks (dashed red line), and the movements due to cyclical shocks (patterned, scale on the right axes). The right panel plots the decomposition of the cyclical component: the dashed graph is fluctuations due to sales shocks, the solid black line is fluctuations due to other output shocks.

Figure 4: The graph plots the decomposition of the path of mean-adjusted cyclical hours per employee. The patterned blue line is the observed path, the red dotted line is fluctuations due to permanent shocks, the solid black line is fluctuations due to sales shocks, and the patterned green line is fluctuations due to other output shocks.

As illustrated in Figures 3 and 4, a large portion of the volatility in employment and hours per employee cannot be explained solely by permanent shocks...
and adjustments to those permanent shocks, as suggested by the sectoral shift hypothesis. Permanent shocks and adjustments to permanent shocks drive most of the dynamics during normal periods, but their relative importance has not increased after 1984, and cyclical shocks still play a significant role in explaining the dynamics of hours and employment over the business cycle, especially during recessions and the periods immediately following recessions. These decompositions are consistent with the just-in-time employment scenario.

4.1.2 The Role of the Impact Coefficients and Estimated Job Losses

A key issue, of course, is to what extent the change in the impact coefficients (i.e.,) in the sensitivity of employment and hours affected the path of employment and hours, and if this change can explain the unusual behavior during the recoveries. In order to shed light on this question and to isolate the effects of each impact coefficient, I perform counterfactual analysis where I only change one of the impact coefficients to its pre-Great Moderation value, and leave all other parameters at their post-GM values. The approach used here is similar in spirit to the approach used by Kim, Morley and Piger (2008), who use counterfactual analysis to analyze the sources of the Great Moderation, and to the approach used by Morley and Singh (2011), who use counterfactual analysis to study the role of inventory mistakes for the reduction in the volatility of output relative to the volatility of sales. Here the counterfactual analysis is performed as follows:

- the pre-GM results were obtained first
- for a given parameter draw from the MH sampler for the second subsample, the impact coefficient of interest was substituted with the mode for the pre-1984 value
- the observed residuals for the draw (obtained using the MH parameter draw) were orthogonalized and fed through the system using the impact coefficient from the first subsample

Figures 5 and 6 below plot the observed series for employment and the the simulated series, and the observed series for hours and the simulated series.

\footnote{For the sake of completeness, I also repeated the same experiment where I only change one set of the autoregressive parameters. The results from the counterfactual analysis when changing the autoregressive parameters and the impact parameters other than $\lambda_{ey}, \lambda_{es}, \lambda_{hs}$ and $\lambda_{hy}$ are available upon request from the author.}
Figure 5: Counterfactual paths for employment. The observed series is plotted in blue. The yellow cloud is the 90% CI for the counterfactual path when the sales impact coefficients are set to their pre-GM values, and the red “cloud” is the 90% CI for the counterfactual path when the non-sales output impact coefficients are set to their pre-GM values. The gray shading indicates NBER recessions, and recoveries are shaded in blue.

Figure 6: Counterfactual paths for hours per employee (mean-adjusted). The observed series is plotted in blue. The yellow cloud is the 90% CI for the counterfactual path when the sales impact coefficients are set to their pre-GM values, and the red “cloud” is the 90% CI for the counterfactual path when the non-sales output impact coefficients are set to their pre-GM values. The gray shading indicates NBER recessions, and recoveries are shaded in blue.
The experiments illustrate the importance of the change in the impact coefficients. If the impact coefficients on employment had not changed, employment would have exhibited patterns similar to those observed prior to 1984: a rapid decline at the start of the recession caused by a negative shock, and a rapid bounce back in response to positive inventory shocks. However, because the impact coefficients did change, the observed series exhibits much smaller responses to non-sales shocks.\textsuperscript{9} As mentioned above, this is particularly evident when large shocks hit the economy, which is exactly the case of recessions and the positive shocks that get the economy out of a recession. Hours per employee are much more procyclical after the break. When holding the impact parameters at their pre-break levels, the hours per employee cycle is much less volatile, and it takes longer for hours to return to their pre-recession levels. Again, these results are in line with the theory that firms have switched to utilizing more flexible labor inputs which allows them to vary the hours worked much more easily, so they do not need to adjust the number of employees.

To give a more clear picture of the importance in the change of the impact coefficients, the next graph shows the behavior of employment during the post-recession periods and the modes for the counterfactual simulation, both converted back to thousands.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{graph.png}
\caption{The graph plots payroll employment in thousands (solid blue line) versus the simulated series with the pre-break value for the impact coefficient of inventories (dashed red line), and the simulated series with the pre-break value for the impact coefficient of sales (patterned green line). The left panel is the recovery from the 1990 recession, the middle panel the recovery from the 2001 recession, and the right panel the recovery from the 2007-2009 recession.}
\end{figure}

The counterfactual analysis confirms that cyclical fluctuations still play an important role in explaining the movements in employment and hours per employee. Sales shocks play a much more important role in explaining employment fluctuations than other output shocks. Combined with the decline of the volatility of output relative to the volatility of sales, the results support a switch to just-in-time utilization of labor resources.

\textsuperscript{9}Even though the AR coefficients did not change, and the cyclical component still plays a very important role and is quite volatile, if one were to look only at the growth rates of employment, the result presented here would lead to a “loss of cyclical” in the employment growth series, which is in line with the findings of Engemann and Owyang.
4.2 Robustness

4.2.1 The Effects of the Great Recession

In the past two years, there has been an ongoing debate if the Great Recession was the end of the Great Moderation, and if it was the start of a more volatile economic climate where the dynamics of macroeconomic variables is significantly different from the dynamics that were observed prior to 2007. To ensure that the results are not distorted by the presence of large outliers and change in dynamics during the past three years, I reestimate the model given by equations (1)-(11), but the second subsample is shorter and ends at 2007Q3. The third column of Table 4 gives the estimates and the standard deviations for the autoregressive and mean parameters for the shorter subsample, and the third row of Table 5 gives the estimates and the standard deviations for the volatilities and the impact coefficients. Not surprisingly, the standard deviations of almost all the estimates are slightly larger when using the second subsample, but none of the parameter estimates change significantly, implying that including the Great Recession data does not distort the results. This is in line with the results obtained by Stock and Watson (2012), who find that the Great Recession was driven by the same dynamics as the the previous two recessions, but the shocks were larger.

4.2.2 Why Focus on Hours Per Employee?

The literature that studies the relationship between output shocks and hours usually focuses on aggregate hours or on hours per capita, not on hours per employee. However, there is much contention about the proper way to model hours and hours per capita, and about the presence of a stochastic or deterministic trend in the series (for a detailed literature review, see, for example, Basistha, 2009, Francis and Ramey, 2009, or Santeulalia-Llopis, 2012). Francis and Ramey’s main criticism of using aggregate hours or aggregate hours per capita and not accounting for a demographic trend will tend to overestimate the effects of permanent technology shocks on transitory hours and bias them upwards. Santeulalia-Llopis, on the other hand, finds that when he allows for preference shocks that are correlated with output shocks, hours per capita respond positively to technology shocks. The UC model used here is immune to those identification issues, because indirectly nests both Francis and Ramey’s model and Santeulalia-Llopis’ model by allowing the trend in employment to have two separate components that are not perfectly correlated (output shocks and “other” shocks). The trend $\kappa_t$ is allowed to mix the demographic and the preference trends, without making it necessary to identify them separately, and this trend does not enter the hours per employee series directly. Note that aggregate hours are decomposed as total employment multiplied by hours per employee, the “other” permanent shocks does not affect this series directly within a period. Furthermore, focusing on hours per employee rather than hours per capita has the advantage that the movements in hours per employee have a direct interpretation based on the theoretical model. If firms want to adjust total
hours (which is the target variable in all standard theoretical models), they can do so by changing the number of employees, changing the hours per employee ("intensity"), or through a combination of both approaches. The series for hours per employee is stationary in both subsamples, which is easily confirmed by standard stationarity or unit root tests. If I allow for the possibility that hours per employee have a time-varying drift or low-frequency movements that might distort the results\textsuperscript{10}, the results do not change significantly. Reestimating the model by changing equation \textsuperscript{11} to

\[
\Phi_4(L)(h_t - \mu_t) = \lambda_{ht}\eta_t + \lambda_{hy}\epsilon_y + \lambda_{hs}\epsilon_s + \lambda_{hc}\epsilon_c + \epsilon_h
\]

where

\[
\mu_t = \mu_{t-1} + \epsilon_{\mu t}
\]

where \(\epsilon_{\mu t}\) is assumed to be Gaussian with variance \(\sigma_{\mu}\) and uncorrelated with all other shocks (following Basistha, 2009), leads to very small estimates for \(\sigma_{\mu}\): 0.051 (0.033) in the first subsample, 0.050 (0.041) in the second subsample, and all the other parameter estimates are virtually identical to those presented in Tables 3 and 4.

Using the BLS index of aggregate weekly hours (cutting the first subsample to 1964q1-1983q4) or Rios-Rull and Santaulalia-Llopis’ measure of aggregate hours (keeping the full sample 1948q1-2011q4) to calculate hours per employee leads to very similar qualitative results. The impact coefficients are different in magnitude (reflecting the scaling of the hours series), but the ratio of the pre-break to the post-break impact coefficients is the same as the ratios obtained using Francis and Ramey’s BLS series for aggregate hours.\textsuperscript{11}

5 Sectoral Results

The results presented in the previous section show that cyclical fluctuations still play an important role at the aggregate level, and they support the switch to just-in-time production at the aggregate level. However, in order to fully distinguish between the competing theories, one would also need to look at disaggregate industry-level data. The sectoral shift hypothesis states that cyclical fluctuations play a declining role in explaining movements in employment, and that if we look at individual sectors, almost all of the movements in employment for the post-break period can be explained by permanent shocks. On the other hand, if jobless recoveries can be explained by organizational restructuring, the changes should be more drastic in industries that have been expanding at fast rates before a recessionary negative shock hits the economy. In order to test the just-in-time hypothesis at the disaggregate level, I look at the four sectors that are emphasized by Groshen and Potter (2003) when explaining the movement

\textsuperscript{10}Therefore assuming that the unit root and stationarity tests did not have correct finite sample size / power.

\textsuperscript{11}Results available upon request.
of jobs across industries: manufacturing (durables and nondurables), finance, and education and health care. If the sectoral shift hypothesis holds, permanent shocks and adjustments to permanent shocks should explain most of the movements in employment in all of the sectors. If the structural reorganization is true, then employment in the finance and health care sector (both very rapidly growing sectors during the second subsample) should be much less responsive to cyclical inventory/non-sales output shocks after the break.

5.1 Manufacturing Sector

The manufacturing sector is particularly interesting because it has been used to show evidence both in favor of the sectoral shift hypothesis (Groshen and Potter, 2003), and in favor of changing labor demand and moving from adjusting labor on extensive margins to adjusting labor on extensive margins (see, for example, Ramey and Vine, 2006, and Hetrick, 2000), which is consistent with switching to just-in-time production. Furthermore, Engemann and Owyang find that most of the change in cyclicality in employment is due to large changes in the manufacturing sector. To distinguish between the competing theories, I estimate the model for the entire manufacturing sector, and for manufacturing of durables and non-durables. The nominal data series for output and sales are obtained from BEA-NIPA and converted to real terms using the industry price deflators, and the employment and hours series were obtained from BLS. The sample size covered the period 1964q1-2011q2, due to the hours series being available only after 1964. Again, the model was estimated using hundred times the log of all the series.

The parameter estimates for the manufacturing sector and its subsectors are given in Appendix 3. The results are similar to those obtained aggregate data, and there are four key results. First, most of the dynamics in both subsamples is driven by permanent shocks and adjustments to permanent shocks, but the relative importance of the permanent shocks has not increased over time. Second, there is a reduction in volatility in all of the cyclical components, and a reduction in the volatility of output relative to the volatility of sales. Third, the increase in the impact coefficients of sales relative to the impact coefficients on inventories is similar, but slightly larger than the increases for aggregate data. Fourth, the estimated impact coefficient of employment on hours per employee is negative in the second subsample. Table 7 also shows that there is no significant reduction or increase in the persistence of the cycles. All of these results support the just-in-time hypothesis. This is consistent with the assumption that due to using more flexible labor inputs firms can adjust hours much more easily than they can adjust payroll employment, they are able to set output closer to sales, and any cyclical shocks affect hours much more than they affect employment. The results are very similar for manufacturing of durables and nondurables.

12Using Francis and Ramey’s series for disaggregated employment by industry leads to similar results.
5.2 Rapidly Growing Sectors with Long Expansions

Employment in the services sector, and in particular in the financial sector exhibited particularly rapid growth after 1984, especially when compared to other industries. The average growth rate for the services sector was 0.756% per quarter, and 0.423% per quarter for the financial sector, and the services sector experienced very long expansions prior to the past three recessions. According to the organizational restructuring theory holds, the recoveries in this sector should be particularly lagged and drawn out. However, Figures 10 and 11 in Appendix 2 illustrate that the dynamics of employment during the past three recoveries was comparable to the dynamics of employment in the manufacturing sectors. The estimates from the formal econometric model, shown in Tables 8 and 9, confirm this. The impact coefficients of non-sales output shocks on hours per employee increase by more than 150% in the second subsample, the impact coefficient of other output shocks on employment decreases by 70%, and the impact coefficient of employment on hours become negative in the second subsample. The increase in the impact coefficients of other output shocks on hours per employee, coupled with the change in the sign of the impact coefficient of employment on hours per employee indicates that in the second subsample, output increases on impact mostly through increasing hours per employee, and not by increasing the number of employees, which is consistent with just-in-time employment practices. It is important to note the change in the impact coefficients is not as drastic as the change in the manufacturing sector, and that even though it is not significant, the variance of permanent shocks increases relative to the variance of cyclical shocks. This means that most of the movements in employment are due to permanent shocks and adjustments to permanent shocks that may include sectoral shifts or organizational restructuring, but that the cyclical component also shows evidence in favor of switching to just-in-time production.

6 Conclusions

In this paper, I investigated the importance of a change in the propagation mechanism of permanent and transitory sales and inventories/ non-sales output shocks for explaining the observed path of employment and hours after 1984. I find that a large part of the movement in employment and hours is still due to cyclical fluctuations, and the relative importance of transitory movements has not changed significantly after 1984.

Most of the change in the dynamics of employment is due to a change in the relative importance of sales shocks. After 1984, sales shocks play a much more important role in explaining the movements in employment, and hours are much more responsive to transitory output shocks. These findings are consistent

13 The model is similar to the model given by equations (1)-(11), only adjusted to reflect the fact that at quarterly frequency, output and sales are roughly equal. The model is described in detail in Appendix 3.
with a shift towards more flexible use of labor inputs. Rather than committing to opening full-time positions, firms can accommodate temporary increases in demand by temporarily increasing hours until sales have picked up enough for the recovery to be considered robust. The results obtained using disaggregated data confirm that firms have switched towards increasing output by increasing hours rather than by increasing employment, meaning that it became easier to increase hours per current employee (or aggregate hours by utilizing part-time employment or temporary employment) rather than by increasing employment. The disaggregated results indicate that most of the change stems from the manufacturing sector, and changes in manufacturing practices may have affected not just inventory management, but also labor demand.

Further extensions of this work will explore the relationship between real economic activity and labor market variables over the entire business cycle, allowing for a distinct recession and recovery phase. In particular, allowing for a distinct recession and recovery phase allows for non-linear responses of employment and does not restrict me to the assumption that positive and negative shocks have the same effect on employment and hours. Also, I plan to endogenize the break date and allow for an additional break, allowing me to explore at what point the dynamics of employment changed, and also allowing me to test if the behavior during the Great Recession and recovery was significantly different from the behavior during the 1990 and 2001 recession.

References


Appendix 1: State-Space Representation

The measurement equation for the model given by equations (1)-(11) is

\[
\begin{bmatrix}
    y_t \\
    s_t \\
    e_t \\
    h_t
\end{bmatrix} =
\begin{bmatrix}
    1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
    1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}
* \beta_t
\]  

(21)

\[\beta_t = [\tau_t \, \kappa_t \, c_{yt-1} \, c_{st-1} \, c_{et-1} \, c_{ht-1}] \] and the transition equation is given by

\[\beta_t = \mu_t + F \beta_t + u_t \]  

(22)

where \(\mu = [\mu_1 \, \mu_2 \, 0 \, 0 \, 0 \, 0 \, 0 \, 0 \, 0 \, 0 \, 0]\)' and \(u_t = [\eta_t \, v_t \, u_{yt} \, 0 \, u_{st} \, 0 \, u_{et} \, 0 \, u_{ht} \, 0]'\) where \(u_{xt}\) is the linear combination of structural shocks corresponding to the right-hand of the equation that defines behavior of the cyclical component of variable \(x\), given by equations (8)-(11). The transition matrix \(F\) is given by

\[
F =
\begin{bmatrix}
    1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 0 & \phi_{y1} & \phi_{y2} & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & \phi_{s1} & \phi_{s2} & 0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & 0 & \phi_{e1} & \phi_{e2} & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & 0 & 0 & \phi_{h1} & \phi_{h2} & 0 & 0 \\
    0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}
\]  

(23)

When hours per capita are assumed to have a time-varying mean, the measurement equation for the estimated model is given by

\[
\begin{bmatrix}
    y_t \\
    s_t \\
    e_t \\
    h_t
\end{bmatrix} =
\begin{bmatrix}
    1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
    1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
    1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}
* \beta_t
\]  

(24)

where \(\beta_t = [\tau_t \, \kappa_t \, \mu_{ht} \, c_{yt-1} \, c_{st-1} \, c_{et-1} \, c_{ht-1}] \) and the transition equation is given by


\[ \beta_t = \mu + F_t + u_t \]  

(25)

where \( \mu = [\mu_1 \mu_2 0 0 0 0 0 0 0 0]' \) and \( u_t = [\eta_t \epsilon_t \eta_t' 0 u_{xt} 0 u_{xt} 0 u_{ht} 0]' \)

where \( u_{xt} \) is the linear combination of structural shocks corresponding to the right-hand of the equation that defines behavior of the cyclical component of variable \( x \), given by equations (9)-(12). The transition matrix \( F \) is given by

\[
F = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \phi_{y1} & \phi_{y2} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \phi_{s1} & \phi_{s2} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \phi_{s1} & \phi_{s2} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_{h1} & \phi_{h2} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}. \]  

(26)

The state-space representation is identical for each subsample. The variance-covariance matrix \( Q \) is equal to \( E[u_t u_t'] \). For the sake of brevity, the equations that describe each element of \( Q \) as a function of the variances of the structural shocks and the impact coefficients is omitted, but it is available upon request from the author.

**Model and State-Space Representation for Services**

Since the services sector does not typically hold physical inventories (at least at the quarterly level), the model is adjusted to reflect that output and sales are equal within a quarter. The new model is given by the following equations:

\[ y_t = \tau_t + c_y \]  

(27)

\[ e_t = \zeta_t + c_e \]  

(28)

\[ h_t = \mu + c_h \]  

(29)

where \( y_t \) is hundred times the logarithm of real GDP, \( e_t \) is the logarithm of employment, and \( h_t \) is the logarithm of aggregate hours per employee. The stochastic trends in employment and output and the permanent shocks have the same interpretation as in the baseline model. The cyclical components are assumed to be stationary, and their dynamics can be described by the following equations:

\[ \Phi_1(L)(y_t - \tau_t) = \lambda_y \eta_t + \epsilon_y. \]  

(30)
\[ \Phi_3(L)(e_t - \tau_t - \kappa_t) = \lambda_{ct} \eta_t + \lambda_{cy} \epsilon_y + \epsilon_e \]  
(31)

\[ \Phi_4(L)(h_t - \mu_3) = \lambda_{ht} \eta_t + \lambda_{hy} \epsilon_y + \lambda_{he} \epsilon_e + \epsilon_h \]  
(32)

where the impact coefficients are also defined as in the baseline model.

The state-space representation for the trivariate model is given by:

\[
\begin{bmatrix}
y_t \\
e_t \\
h_t
\end{bmatrix} = \begin{bmatrix}
1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix} \beta_t
\]  
(33)

\[ \beta_t = [\tau_t \kappa_t c_y \epsilon_{y-1} \epsilon_t \epsilon_{t-1} c_h \epsilon_{h-1}] \] and the transition equation is given by

\[ \beta_t = \mu_t + F \beta_t + u_t \]  
(34)

where \( \mu = [\mu_1 \mu_2 0 0 0 0 0 0]' \) and \( u_t = [\eta_t v_t u_{yt} 0 u_{et} 0 u_{ht} 0]' \) where \( u_{xt} \) is the linear combination of structural shocks corresponding to the right-hand side of the equation that defines behavior of the cyclical component of variable \( x \), given by equations (21)-(23). The transition matrix \( F \) is given by

\[ F = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \phi_{y1} & \phi_{y2} & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \phi_{c1} & \phi_{c2} & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \phi_{h1} & \phi_{h2} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix} \]  
(35)

Appendix 2: Bayesian Estimation

The results presented in the text are obtained using a multi-block Metropolis-Hastings algorithm with a tailored proposal distribution. In order to ensure identification, I had to restrict the sign of \( \lambda_{y\eta} \) and \( \lambda_{s\eta} \). Assuming that \( \lambda_{y\eta} \) and \( \lambda_{s\eta} < 0 \) is fairly innocuous in this context and is in line with previous studies, as discussed below. For convenience, the prior for \( \lambda_{y\eta} \) and \( \lambda_{s\eta} \) were truncated normal distributions on \((-\infty, 0)\) with mean \(-0.5\) and variance equal to 1, and the prior for \( \lambda_{ys} \) was a truncated normal distribution on \((0, \infty)\) with mean 1 and variance 1. These priors are based on the MLE estimates and on results of previous studies (for example, Morley et al., 2003, Sinclair 2009, Morley and Singh, 2011, or Basistha, 2009), that show that the correlation between the permanent and the transitory shocks of output is negative and large in absolute value, and that most of the volatility in output and sales comes from permanent movements. Restricting \( \lambda_{ys} \) to be positive simply means that output responds
positively to positive sales shocks. This restriction is based on the MLE estimates and is consistent both with theory and with estimated responses from a basic VECM models. It is important to note that the truncated priors are merely a convenient tool to ensure slightly faster convergence— the results were robust to the choice of priors, and using more diffuse priors or different families of priors does not affect the results significantly. The only restriction that is needed to identify the coefficients is the sign restrictions.

The priors for the initial values for the stochastic trends were Gaussian distributions that were centered at the initial observations and had variance equal to 10. The MH algorithm was implemented as follows:

1. Start with arbitrary values for the parameter coefficients.
2. Conditional on the parameter coefficients, obtain the smoothed estimates for the state variables.
3. At the $i^{th}$ iteration, conditional on the parameter vector $\theta^{(i)}$ and the state variables, draw a new value for the J-dimensional parameter block $\theta_b$ from a Student-t proposal with mean $\theta_b^{(i)}$, scale equal to the J-by-J subblock of the inverse of the Hessian matrix evaluated at $\theta^{(i)}$ and 15 degrees of freedom. If the value is accepted, update $\theta_i$ to reflect the update when calculating the Hessian for the other blocks.
4. Repeat step 2 until all parameters are updated, update $\theta^{i+1}$

The results presented in the text were obtained using 80,000 iterations of the MH chain, after a burn-in of 20,000 draws. To ensure convergence, the chain was started from several different values. In order to obtain the trend and cycle estimates, I use the Kalman filter and the related prediction-error decomposition.
Appendix 3: Parameter Estimates for Industry-Level Data

Manufacturing

Table 7: Sums of the estimated AR coefficients - Manufacturing

<table>
<thead>
<tr>
<th>Total Manufacturing</th>
<th>Durables</th>
<th>Nondurables</th>
</tr>
</thead>
<tbody>
<tr>
<td>1964q1+1983q4</td>
<td>1984q1+2011q2</td>
<td>1964q1+1983q4</td>
</tr>
<tr>
<td>( \phi_{y1} + \phi_{y2} )</td>
<td>0.788 (0.120)</td>
<td>0.777 (0.045)</td>
</tr>
<tr>
<td>( \phi_{s1} + \phi_{s2} )</td>
<td>0.811 (0.012)</td>
<td>0.805 (0.120)</td>
</tr>
<tr>
<td>( \phi_{h1} + \phi_{h2} )</td>
<td>0.781 (0.114)</td>
<td>0.869 (0.120)</td>
</tr>
</tbody>
</table>

Table 8: Estimated Variances and Impact Coefficients, Manufacturing Sector

<table>
<thead>
<tr>
<th>Manufacturing-aggregate</th>
<th>Durables</th>
<th>Nondurables</th>
</tr>
</thead>
<tbody>
<tr>
<td>1964q1+1983q4</td>
<td>1984q1+2011q2</td>
<td>1964q1+1983q4</td>
</tr>
<tr>
<td>( \sigma_\eta )</td>
<td>0.2680 (0.023)</td>
<td>1.044 (0.062)</td>
</tr>
<tr>
<td>( \sigma_v )</td>
<td>0.2901 (2.257)</td>
<td>2.012 (0.019)</td>
</tr>
<tr>
<td>( \sigma_y )</td>
<td>1.026 (0.142)</td>
<td>0.824 (0.004)</td>
</tr>
<tr>
<td>( \sigma_s )</td>
<td>1.255 (0.132)</td>
<td>0.700 (0.062)</td>
</tr>
<tr>
<td>( \sigma_e )</td>
<td>0.801 (0.126)</td>
<td>1.055 (0.052)</td>
</tr>
<tr>
<td>( \sigma_h )</td>
<td>0.817 (0.111)</td>
<td>0.414 (0.002)</td>
</tr>
<tr>
<td>( \rho_{\eta\eta} )</td>
<td>-0.708 (0.211)</td>
<td>-0.697 (0.223)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>-0.751 (0.124)</td>
<td>-0.627 (0.005)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>-0.678 (0.012)</td>
<td>-0.675 (0.032)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>-0.318 (0.049)</td>
<td>-0.328 (0.005)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>-0.305 (0.010)</td>
<td>-0.117 (0.018)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>0.8656 (0.043)</td>
<td>0.772 (0.007)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>0.1790 (0.025)</td>
<td>0.028 (0.006)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>0.210 (0.010)</td>
<td>0.026 (0.117)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>0.157 (0.055)</td>
<td>0.301 (0.133)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>0.221 (0.104)</td>
<td>0.225 (0.014)</td>
</tr>
<tr>
<td>( \lambda_{\eta\eta} )</td>
<td>0.196 (0.041)</td>
<td>0.207 (0.174)</td>
</tr>
</tbody>
</table>
Figure 8: Employment in the manufacturing sector after the NBER trough.

The left panel plots total employment in manufacturing, the middle panel plots employment in manufacturing of durables, and the right panel plots employment in manufacturing of nondurables. The blue lines are the average of recoveries before 1984, the red dashed lines are the recovery from the 1990 recession, the green dot-dash lines are the recovery from the 2001 recession, and the patterned black lines are the recovery from the Great Recession.

**Services and Financial Services**

Table 9: Sums of the estimated AR coefficients

<table>
<thead>
<tr>
<th></th>
<th>Services 1964q1-1983q4</th>
<th>Services 1984q1-2011q2</th>
<th>FIRE 1964q1-1983q4</th>
<th>FIRE 1984q1-2011q2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi_y1 + \phi_y2$</td>
<td>0.700 (0.118)</td>
<td>0.801 (0.199)</td>
<td>0.953 (0.069)</td>
<td>0.843 (0.164)</td>
</tr>
<tr>
<td>$\phi_e1 + \phi_e2$</td>
<td>0.782 (0.125)</td>
<td>0.889 (0.073)</td>
<td>0.836 (0.087)</td>
<td>0.987 (0.018)</td>
</tr>
<tr>
<td>$\phi_h1 + \phi_h2$</td>
<td>0.802 (0.158)</td>
<td>0.862 (0.158)</td>
<td>0.873 (0.143)</td>
<td>0.755 (0.206)</td>
</tr>
</tbody>
</table>
### Table 10: Estimated Variances and Impact Coefficients, Services Sector

<table>
<thead>
<tr>
<th></th>
<th>1964q1–1983q4</th>
<th>1984q1–2011q2</th>
<th>1964q1–1983q4</th>
<th>1984q1–2011q2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_y$</td>
<td>1.243 (0.156)</td>
<td>1.217 (0.234)</td>
<td>2.451 (0.021)</td>
<td>2.136 (0.354)</td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td>2.073 (0.560)</td>
<td>3.487 (0.412)</td>
<td>1.998 (0.058)</td>
<td>1.978 (0.357)</td>
</tr>
<tr>
<td>$\sigma_y$</td>
<td>2.451 (0.021)</td>
<td>1.998 (0.058)</td>
<td>1.978 (0.357)</td>
<td></td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td>1.217 (0.234)</td>
<td>2.451 (0.021)</td>
<td>2.136 (0.354)</td>
<td></td>
</tr>
<tr>
<td>$\rho_{\eta\eta}$</td>
<td>-0.750 (0.300)</td>
<td>-0.319 (0.210)</td>
<td>-0.836 (0.144)</td>
<td>-0.362 (0.115)</td>
</tr>
<tr>
<td>$\lambda_{y\eta}$</td>
<td>-0.469 (0.129)</td>
<td>-0.028 (0.012)</td>
<td>-0.672 (0.160)</td>
<td>-0.725 (0.215)</td>
</tr>
<tr>
<td>$\lambda_{v\eta}$</td>
<td>-0.102 (0.142)</td>
<td>-0.180 (0.178)</td>
<td>-0.128 (0.034)</td>
<td>-0.175 (0.087)</td>
</tr>
<tr>
<td>$\lambda_{y\eta}$</td>
<td>-0.170 (0.113)</td>
<td>-0.244 (0.075)</td>
<td>-0.138 (0.007)</td>
<td>-0.105 (0.036)</td>
</tr>
<tr>
<td>$\lambda_{v\eta}$</td>
<td>0.370 (0.005)</td>
<td>0.121 (0.014)</td>
<td>0.383 (0.125)</td>
<td>0.067 (0.032)</td>
</tr>
<tr>
<td>$\lambda_{y\eta}$</td>
<td>0.286 (0.041)</td>
<td>0.475 (0.050)</td>
<td>0.362 (0.046)</td>
<td>0.444 (0.065)</td>
</tr>
<tr>
<td>$\lambda_{v\eta}$</td>
<td>0.278 (0.112)</td>
<td>-0.048 (0.071)</td>
<td>0.322 (0.054)</td>
<td>-0.165 (0.045)</td>
</tr>
</tbody>
</table>

Figure 9: Industry employment after the NBER trough (Indexed to Prerecession Level). The left panel plots aggregate employment in services, the right panel plots employment in the FIRE sector. The blue lines are the average of recoveries before 1984, the red dashed lines are the recovery from the 1990 recession, the green dot-dash lines are the recovery from the 2001 recession, and the patterned black lines are the recovery from the Great Recession.