Keywords: Structural Unemployment, Sectoral vs. Aggregate Shocks, Dynamic Factor Analysis.
Subject Classifications: E24, J21, C22.

* Address for correspondence Paul Oslington, Professor of Economics, Australian Catholic University, Edward St, North Sydney, NSW 2060, Australia.
Ph: 61 2 9739 2868 Email pauloslington@gmail.com
We thank Randy Ilg of the Bureau of Labour Statistics for his prompt and helpful responses to many queries about the data.

Abstract
The relative merits of microeconomic and macroeconomic models of phenomena such as unemployment has been a topic of enduring debate among economists. This paper sheds light on this issue via a statistical analysis of the contributions of industry-sectoral micro shocks vs aggregate macro shocks to US unemployment movements. Sectoral shocks are found to account for around half of post-war movements in US unemployment, and tend to be of higher frequency than the common shocks, and concentrated in the service and manufacturing sectors. Frequencies, sectoral patterns and flows provide clues to the identity of some of the shocks driving unemployment. For certain periods, such as the rise in unemployment in the 1970s, common shocks were dominant, but sectoral shocks have become more important in recent years. We conclude that micro or sectoral models deserve more attention, alongside the more popular aggregate models of unemployment.
1) Introduction

The causes of unemployment have been a matter of longstanding dispute in economics. Many different theories have been proposed, and disputes over policy at times have been acrimonious. Effective policy depends on understanding the causes of unemployment movements. A fundamental question is whether these causes are sector-specific or common to all sectors. If sectoral shocks are more important than aggregate shocks then we need “micro” models and policy interventions which focus on the relevant sectors. If not then the focus should be on aggregate “macro” models and interventions.

Most theoretical models of unemployment are highly aggregate single sector models, despite the general movement in macroeconomics to models based on individual behaviour (Layard, Nickell and Jackman (2005), Yashiv (2007)). However, there exist a variety of disaggregate or “micro” models where sector specific shocks drive unemployment movements. Lucas and Prescott's (1974) seminal paper showed how orthogonal product demand sectoral shocks and a search across spatially separated markets generate unemployment. Rogerson (1987) developed this further in a two period, two sector setting, and Long and Plosser (1983) constructed a sectoral shock real business cycle model. Ljungqvist and Sargent's (1998) influential ‘turbulence plus skill decay’ account of European unemployment is from this family of models. There are many possible shock generating mechanisms, such as demographic adjustment in Matsuyama (1992) and informational asymmetries in Riordan and Staiger (1993). Robert Hall (2003; 2005) suggests further possible sectoral shock models of unemployment. Any general equilibrium trade model with unemployment (e.g. Matusz (1996), Oslington (2005), Melitz and Cunat (2006)) is also a sectoral model of unemployment.

Empirically, the most common approach has been to test the restrictions implied by particular models of unemployment. Some of the above models have performed reasonably well. However, while this is encouraging, the statistical significance of particular parametric restrictions does not necessarily help to resolve the broader question of whether unemployment is primarily an aggregate, or a sectoral, phenomenon. An alternative empirical strategy is to estimate the contribution of sectoral factors while remaining agnostic about the particular sectoral shock or adjustment mechanism. The much cited study of Lilien (1982) attempted to do this by adding an index of the sectoral dispersion of employment to a macroeconomic model. Other researchers have pointed out that his index of sectoral employment variation is problematic (see, for example, Abraham and Katz (1986), and Murphy and Topel (1987)), making interpretation of his results difficult. In our opinion though, the
main difficulty with Lilien’s paper is that the credibility of the estimates depends to some extent on
the validity of the monetary macroeconomic model to which the sectoral variation index is added.
While this model was state-of-the-art at the time that Lilien conducted his research, it now looks quite
dated.

This paper considers the contribution of sectoral and aggregate shocks to post war US unemployment
movements. Rather than testing the restrictions implied by particular theoretical models, our method
is to employ dynamic factor analysis (Geweke (1977) and Sargent and Sims (1977)) to measure the
variance of sectoral and aggregate components identified by orthogonality conditions. Our interest is
not in testing particular hypotheses to confirm or repudiate any particular theoretical model of
unemployment, but instead to compile some stylised facts about the behaviour of unemployment,
which will provide a guide to policy makers and theorists with an interest in the field.

Some other studies have measured the contribution of sectoral shocks to US variables using broadly
similar methodologies. Long and Plosser (1987) used factor analysis techniques on output for sub-
sectors of US manufacturing from 1948 to 1981 to assess the importance of sectoral shocks. Norrbin
and regional components using the Engle-Watson DYMIMIC factor analysis techniques. Forni and
Lippi (1997) and Forni and Reichlin (1998) considered very finely disaggregated US manufacturing
output for the period 1958-86 using their own dynamic factor techniques.

In contrast to previous work on sectoral shocks, we focus directly on unemployment rather than
output or employment movements. There are several reasons for this. Firstly, using unemployment
data focuses attention on the shocks that affect workers who remain unemployed, who are of most
policy concern. Secondly, unemployment has its own dynamics influenced by, but often diverging
from, employment and output dynamics (as emphasised by Hall (1999 p1150) or Stock and Watson
(1999)). Thirdly, the natural restrictions on flows that come from using unemployment by industry
data give us some clues to the identity of the common and sectoral shocks.

Our aim is to quantify the contribution of various kinds of shocks, enrich existing accounts of the
post-war evolution of US unemployment, and suggest which kinds of models and policies – macro or
micro - we should be focusing on in disputes over unemployment.
2) Data

Data on unemployment by industry sector are available from the US Bureau of Labour Statistics (BLS)\(^1\). As part of the Current Population Survey (CPS) the unemployed are asked the last industry they worked in. Those with no previous work experience are recorded as not attached to any industry.

Sectoral unemployment rates are defined as unemployed persons in the sector divided by the sum of unemployed and employed persons in the sector. Sectoral contributions to unemployment are unemployed persons in the sector divided by total unemployed and employed persons in all sectors, so that the sectoral contributions (including the unattached sector) sum to the overall rate of unemployment. We will work with the sectoral contributions rather than sectoral unemployment rates to reduce possible measurement errors associated with the sectoral employed persons data series.

The data are monthly for the period January 1948 to December 2002. In 2003 the Standard Industry Classification (SIC) was replaced by the North American Industry Classification System (NAICS), creating what the BLS series notes describe as “a complete break in comparability with existing data series at all levels of occupation and industry aggregation”.

We work with the ten BLS major industry groups: Agriculture (AG), Mining (MIN), Manufacturing (MAN), Construction (CON), Transport and Public Utilities (TU), Wholesale and Retail Trade (TRADE), Finance with Insurance and Real Estate (FIN), Services (SERV), and Public Administration (PUB) and Not Attached (N).

The series that we use have been seasonally adjusted by the BLS, and we have taken first differences and rescaled to a zero mean.

The greater the aggregation of sectors, the more likely are shocks to be confined to a sector and hence the higher will be the estimated contribution of sectoral shocks to unemployment movements. Ten sectors is a natural level of aggregation in the data which allows comparison with other studies of sources of output and employment fluctuations.

\(^1\) Available on the BLS web site at http://stats.bls.gov. Similar data are available for other countries although the time series are not as long as for the US, and differences in definitions across countries make comparisons difficult.
3) MODEL

Our empirical model is intended to be quite general. Our objective is to estimate the common and sectoral contributions to overall employment without imposing a particular theory of unemployment or the business cycle on the data.

It is assumed that sectoral contributions to unemployment are driven by an unobservable stochastic process which is unique to that sector, together with one or more unobservable stochastic processes that are common to all sectors, so that

\[
\begin{align*}
    u_t &= \sum_{j=0}^{\infty} B_j c_{t-j} + s_t \\
    w' u_t &= w' \left( \sum_{j=0}^{\infty} B_j c_{t-j} + s_t \right) \\
    u_t &= \sum_{j=0}^{\infty} B_j c_{t-j} + s_t \\
    u_t &= \sum_{j=0}^{\infty} B_j c_{t-j} + s_t
\end{align*}
\]

where \( u_t \) is a \( px1 \) vector of sectoral contributions to unemployment.

\( c_t \) is a \( kx1 \) vector of weakly stationary common shocks where \( k \) is the number of common components.

\( B_j \) is a sequence of \( pxk \) matrices of coefficients capturing the effect of each of the common components on unemployment in each sector at all time lags.

\( s_t \) is a \( px1 \) vector of weakly stationary sector-specific shocks.

Summing these sectoral contributions gives the aggregate unemployment rate:

\[
U_t = w' u_t
\]

where \( w \) is a \( px1 \) unit vector. There is no need for a vector of sectoral weights because we work with sectoral contributions to aggregate unemployment rather than sectoral unemployment rates.

The remainder of the specification of the model is motivated by the need for statistical identification and computational tractability. There exist a couple of approaches which could be followed. One approach is to specify autoregressive processes for the common and idiosyncratic components of the model. Engle and Watson (1981) detail a scoring algorithm based on the Kalman filter which may be used to estimate such a model. Watson and Engle (1983) and Shumway and Stoffer (1982) propose an EM algorithm as an alternative to scoring. A shortcoming of this approach is the need to specify finite orders for the autoregressive components of the model, and the need to approximate the infinite sums in Equation (1) by choosing finite orders for the distributed lags. An alternative approach, proposed by Geweke (1977) and Sargent and Sims (1977) is to divide the spectrum into a set of non-overlapping frequency bands, to assume that the
spectrum is constant within each band, and to employ likelihood methods to fit the factor model in each of the frequency bands.

Let $z'_t = (c'_t, s'_t)$. We assume that $E(z_t) = 0$ and that $E(z_t z'_{t-j})$ is a diagonal matrix for all $j$. Serial correlation in the elements of $z_t$ is permitted subject to the restriction that $z_t$ is weakly stationary.

Under these assumptions, inserting Wold moving average representations of $c_t$ and $s_t$ in Equation (1) yields:

$$u_t = \sum_{j=0}^{\infty} \Lambda_j \varepsilon_{t-j} + \sum_{j=0}^{\infty} \Psi_j \eta_{t-j}$$

where $\Lambda_j, j \in \mathbb{Z}$ is a sequence of $p \times k$ matrices of moving average coefficients for the common component $\Psi_j, j \in \mathbb{Z}$ is a sequence of $p \times p$ diagonal matrices of moving average coefficients for the sectoral component, and all elements of the $k \times 1$ vector $\varepsilon_t$ and $p \times 1$ vector $\eta_t$ are mutually uncorrelated white noise processes.

The autocovariance function of $u_t$ is

$$\Gamma_u(r) = \sum_{j=0}^{\infty} \left( \Lambda_j \Lambda'_{t-r} + \Psi_j \Psi'_{t-r} \right) \quad r = 0, 1, 2, \ldots$$

The Fourier transform of the autocovariance function of the vector of sectoral unemployment rates is

$$F(\omega) = \sum_{v=-\infty}^{\infty} \sum_{j=0}^{\infty} \Lambda_j \Lambda'_{v-j} e^{-iv\omega} + \sum_{v=-\infty}^{\infty} \sum_{j=0}^{\infty} \Psi_j \Psi'_{v-j} e^{-iv\omega}$$

$$= \tilde{\Lambda}(\omega) \tilde{\Lambda}^H(\omega) + \tilde{\Psi}(\omega) \tilde{\Psi}^H(\omega) \quad |\omega| \leq \pi$$

where $\tilde{\Lambda}(\omega)$ and $\tilde{\Psi}(\omega)$ are the Fourier transforms of $\Lambda_j$ and $\Psi_j$ respectively and $^H$ signifies the complex conjugate transpose.
Given T observations on \( u_t \) (where T is even), the discrete Fourier transform of \( u_t \) at the \( \frac{T}{2} + 1 \) harmonic frequencies is

\[
\tilde{u} \left( \frac{2\pi j}{T} \right) = T^{-\frac{1}{2}} \sum_{t=0}^{T-1} u_t e^{j2\pi j t / T} \quad j = 0, \ldots, \frac{T}{2}
\]

From this, the periodogram ordinates are

\[
I \left( \frac{2\pi j}{T} \right) = \tilde{u} \left( \frac{2\pi j}{T} \right) \tilde{u} \left( \frac{2\pi j}{T} \right)^H \quad j = 0, \ldots, \frac{T}{2}
\]

The domain of \( I \left( \frac{2\pi j}{T} \right) \) is divided into m non-overlapping frequency bands. The spectral density is assumed to be constant in each frequency band, and is estimated as

\[
S_k = \frac{1}{T^\text{max}_k - T^\text{min}_k + 1} \sum_{j = T^\text{min}_k}^{T^\text{max}_k} I \left( \frac{2\pi j}{T} \right) \quad k = 1, \ldots, m
\]

where \( \frac{2\pi T^\text{min}_k}{T} \) is the lowest harmonic frequency in band k, and \( \frac{2\pi T^\text{max}_k}{T} \) is the highest.

Assuming that \( \epsilon_t \) and \( \eta_t \) are Gaussian, the log-likelihood for frequency band k may be written as

\[
\ln L_k \propto -\left( \ln |F_k| + \text{tr} \left( S_k F_k^{-1} \right) \right) \quad k = 1, \ldots, m
\]

where \( F_k = \tilde{\Lambda}_k \tilde{\Lambda}_k^H + \tilde{\Psi}_k \tilde{\Psi}_k^H \), \( \tilde{\Lambda}_k \) is the pxk matrix of factor loadings for frequency band k, and \( \tilde{\Psi}_k \) is the diagonal pxp matrix of coefficients for the sector-specific processes in frequency band k.

Geweke (1977) provides details of a Fletcher-Powell algorithm for maximising the likelihood. This approach is similar to that proposed for the static factor model by Joreskog (1967). Rather than using this algorithm, in the present paper we implement an EM algorithm. Our algorithm is a simple extension to complex valued matrices of the EM algorithm constructed for static factor models by Rubin and Thayer (1982), and the reader is referred to their paper for technical details. This has the advantages of being relatively simple to code and of having robust, albeit possibly slow, convergence (Dempster, Laird and Rubin (1977)).
5) THE RESULTS

The discrete Fourier transform of the data yielded 330 periodogram ordinates between 0 and $\pi$. These were divided into five frequency bands and the factor model fitted to each band. An advantage of the technique we are using is that we can test for the number of common factors in each frequency band, using a likelihood ratio test. The test statistic has a $\chi^2$ distribution with $\left[ (p - k)^2 - p \right]$ degrees of freedom. Test statistics for the goodness of fit of the model are presented in Table 2. At a significance level of 5% the restriction that there is one common factor was not rejected.

Table 2 - Goodness of fit tests

<table>
<thead>
<tr>
<th>Frequencies</th>
<th>Ordinates</th>
<th>Cycles per year</th>
<th>1 factor model $\chi^2(71)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 0.2$\pi$</td>
<td>1:66</td>
<td>0 - 1.2</td>
<td>77.8</td>
</tr>
<tr>
<td>0.2$\pi$ - 0.4$\pi$</td>
<td>67:132</td>
<td>1.2 - 2.4</td>
<td>49.9</td>
</tr>
<tr>
<td>0.4 $\pi$ - 0.6 $\pi$</td>
<td>133:198</td>
<td>2.4 - 3.6</td>
<td>56.0</td>
</tr>
<tr>
<td>0.6$\pi$ - 0.8$\pi$</td>
<td>199:264</td>
<td>3.6 - 4.8</td>
<td>26.9</td>
</tr>
<tr>
<td>0.8 $\pi$ - $\pi$</td>
<td>265:330</td>
<td>4.8 - 6</td>
<td>47.6</td>
</tr>
</tbody>
</table>

The proportion of the variance of the overall unemployment rate that is accounted for by common shocks is estimated as

$$w' \left( \sum_{k=1}^{m} \tilde{\Lambda}_k \tilde{\Lambda}_k^H \right) w$$

(10)

$$w' \left( \sum_{k=1}^{m} S_k \right) w$$

where $\tilde{\Lambda}_k$ is the maximum likelihood estimate of $\tilde{\Lambda}_j$, and $w$ is a px1 vector of ones. Table 3 shows the decomposition of variation in unemployment across frequency bands for the common and sector-specific components.
Table 3 – Variance decomposition of overall unemployment rate

<table>
<thead>
<tr>
<th>Cycles pa</th>
<th>Common %</th>
<th>Sectoral %</th>
<th>Total %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1.2</td>
<td>35</td>
<td>2</td>
<td>37</td>
</tr>
<tr>
<td>1.2-2.4</td>
<td>4</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>2.4-3.6</td>
<td>2</td>
<td>11</td>
<td>13</td>
</tr>
<tr>
<td>3.6-4.8</td>
<td>4</td>
<td>14</td>
<td>18</td>
</tr>
<tr>
<td>4.8-6</td>
<td>5</td>
<td>16</td>
<td>21</td>
</tr>
<tr>
<td>Total %</td>
<td>51</td>
<td>49</td>
<td>100</td>
</tr>
</tbody>
</table>

Overall, 51% of the variation in unemployment is accounted for by common shocks. The magnitude is similar to Lilien’s (1982 p778) finding that “as much as half of the variance of unemployment over the post-war period can be attributed to …slow adjustment of labour to shifts in employment between sectors”. It is also not too far away from the previous factor analytic work of Long and Plosser (1987) who attributed 63 percent of movements in US output 1948-81 to sectoral factors and Forni and Reichlin (1998) who found 60 percent of the variation of US output from 1958 to 1986 to be sectoral. Comparisons with these studies cannot be pushed too far because they consider output rather than unemployment, different periods, and different sets of industries and levels of aggregation.

The restrictions on flows in and out of sectoral unemployment discussed earlier lead us to believe our estimate is a lower bound for the contribution of sectoral shocks. An adverse sectoral shock to an industry pushes workers into that sector’s unemployment pool, but a shock which boosts a sector will draw workers out of all sectors, and such a boosting shock is likely to be measured as a common shock. Our estimate of the contribution of common shocks will this include some boosting sectoral shocks. This effect will be greater the greater is intersectoral mobility of labour.

While our overall estimate of the contribution of sectoral shocks to unemployment movements is at least half, the split between the common and sectoral shocks varies greatly across frequencies. The low frequency variation (including the business cycle frequencies of around 0.25 cycles per annum) unemployment is driven almost entirely by common shocks. At higher frequencies sectoral shocks dominate. This is consistent with the finding of Forni and Reichlin (1998 p471) that sectoral shocks to US output tend to be high frequency.

The breakdown by sector of the sectoral contributions to unemployment movements is shown in table 4. Our results are consistent with the well documented long term reallocation of labour from
manufacturing to services. Manufacturing, Trade and Services are the largest contributors, but these are also the largest sectors. If we adjust for size by dividing sectoral contributions by sectors proportions of employment, then construction, agriculture and mining are the most volatile. Manufacturing is far more volatile than the other large contributors trade and services. Stock and Watson (1999 p39-40) find similar industry volatility patterns in post-war US employment data. Interestingly, the public sector is of comparable volatility to manufacturing, although this may be due to the influence of short term public sector job creation programs, rather than volatility of core public sector employment.

Table 4 - Contribution of each sector to variance of overall unemployment rate

<table>
<thead>
<tr>
<th>Sector</th>
<th>Contribution %</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>AG</td>
<td>1.9</td>
<td>0.7</td>
</tr>
<tr>
<td>MIN</td>
<td>1.3</td>
<td>3.3</td>
</tr>
<tr>
<td>MAN</td>
<td>9.6</td>
<td>0.6</td>
</tr>
<tr>
<td>CON</td>
<td>4.6</td>
<td>0.7</td>
</tr>
<tr>
<td>TRANS UT</td>
<td>1.7</td>
<td>0.2</td>
</tr>
<tr>
<td>TRADE</td>
<td>7.1</td>
<td>0.3</td>
</tr>
<tr>
<td>FIN</td>
<td>0.7</td>
<td>0.1</td>
</tr>
<tr>
<td>SERV</td>
<td>5.9</td>
<td>0.2</td>
</tr>
<tr>
<td>PUB</td>
<td>2.6</td>
<td>0.6</td>
</tr>
<tr>
<td>N</td>
<td>13.6</td>
<td></td>
</tr>
<tr>
<td>Total %</td>
<td>49.0</td>
<td></td>
</tr>
</tbody>
</table>

6) RESULTS FOR SUB-PERIODS

A question of interest is whether there are periods in which sectoral shocks were particularly important. We divided our data into three sub-periods, firstly the long post-war boom to 1969, secondly the rise in unemployment from 1970 through to 1983, and the subsequent period of strong growth from 1984 to end of our sample in 2002. Again we tested the goodness of fit for the sub-period models, and Table 5 indicates the single common factor specification was not rejected for any sub-period.
The breakdown of movements in unemployment into common and sectoral components is given in Table 6. It is striking how dominant common shocks were during the large rise of unemployment in the 1970s, explaining 64% of the variations from 1970-83, with a complete reversal for the 1984-2002 years of growth and falling unemployment when common shocks only explained 30% of the variation. The declining importance of macro volatility we find in unemployment is consistent with the recent work of Comin and Mulani (2006).

### Table 6 – Variance decomposition of overall unemployment rate for sub-periods

<table>
<thead>
<tr>
<th>Cycles Pa</th>
<th>Common</th>
<th>Sectoral</th>
<th>Total</th>
<th>Common</th>
<th>Sectoral</th>
<th>Total</th>
<th>Common</th>
<th>Sectoral</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Jan48 –Dec69</td>
<td></td>
<td></td>
<td>Jan70 –Dec83</td>
<td></td>
<td></td>
<td>Jan84 –Dec02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-2</td>
<td>37</td>
<td>5</td>
<td>42</td>
<td>51</td>
<td>4</td>
<td>55</td>
<td>23</td>
<td>8</td>
<td>31</td>
</tr>
<tr>
<td>2-4</td>
<td>5</td>
<td>13</td>
<td>18</td>
<td>8</td>
<td>13</td>
<td>21</td>
<td>6</td>
<td>24</td>
<td>30</td>
</tr>
<tr>
<td>4-6</td>
<td>17</td>
<td>24</td>
<td>40</td>
<td>5</td>
<td>19</td>
<td>24</td>
<td>0</td>
<td>38</td>
<td>38</td>
</tr>
<tr>
<td>Total %</td>
<td>59</td>
<td>41</td>
<td>100</td>
<td>64</td>
<td>36</td>
<td>100</td>
<td>30</td>
<td>70</td>
<td>100</td>
</tr>
</tbody>
</table>
The sectoral contributions for the sub-periods are given in Table 7. The sectors contributing most in the 1984-2002 sub-period are trade and services, with a large jump in N-sector shocks, which we interpreted as labour supply shocks.

Table 7 - Contribution of each sector to variance of overall unemployment rate for sub-periods

<table>
<thead>
<tr>
<th>Sector</th>
<th>Jan48 –Dec69</th>
<th>Jan70 –Dec83</th>
<th>Jan84 –Dec02</th>
</tr>
</thead>
<tbody>
<tr>
<td>AG</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>MIN</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>MAN</td>
<td>10</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>CON</td>
<td>4</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>TRANS UT</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>TRADE</td>
<td>5</td>
<td>5</td>
<td>13</td>
</tr>
<tr>
<td>FIN</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>SERV</td>
<td>4</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>PUB</td>
<td>1</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>N</td>
<td>11</td>
<td>13</td>
<td>19</td>
</tr>
<tr>
<td>Total %</td>
<td>41</td>
<td>36</td>
<td>70</td>
</tr>
</tbody>
</table>

7) DISCUSSION

Our model is purely statistical and does not facilitate the testing of particular theoretical models of unemployment. Nonetheless, it is of interest to informally consider what the common and sectoral factors might be.

Some possible candidates for the common factor are:
- Technological change which affects all sectors.
- Effective demand variations.
- Institutional changes affecting the whole economy.
- Macroeconomic policy.

Some candidates for the sectoral factors are:
- Technological change which is specific to a sector, including new products.
- Changes in the pattern of demand across sectors.
- Institutional changes affecting particular sectors.
- Microeconomic policy.
• Trade changes, reflected in relative world commodity prices.

Do any of our factors look like technological change? There is little consensus among theorists of technological change to guide us about the frequency of the process, but is often thought to be fairly low frequency. Crespo (2005) for instance finds US Solow residuals concentrated at a frequency of 7 to 11 years, although the Solow residual data series is annual so such studies will miss any high frequency technological variation. A different type of evidence is provided Forni and Reichlin (1998 pp465-66) who use an ingenious method (technology shocks must increase output) to identify as technology one of their two common factors driving sub-sectoral variation post-war US manufacturing output. This technological common factor is low frequency, so if their identification is sound it provides further evidence that technological generates low frequency variation. Technological change is a plausible candidate for our low frequency common factor. Technological change may also generate some the high frequency variation behind the sectoral factors, but existing work with structural models gives us no hard evidence on this.

There is even less evidence in the theoretical or structural estimation literatures about the frequency of effective demand shocks that would allow us to assess their plausibility as a candidate common shock.

Institutional and policy changes are low frequency events, and therefore plausible candidates for the common shock. The high frequency of the estimated sectoral factor makes industry specific policy change an implausible candidate for the sectoral factor. If institutional and policy changes are important for unemployment (as for instance argued by Layard Nickell and Jackman 2005) then it is the changes which affect the whole economy, such as changes to the tax and welfare system, which are important rather than industry policy or trade policy. Our results give little comfort to those who advocate subsidies or support for particular industries as a cure for unemployment.
The particular pattern of unemployment by industry net flows illustrated in Figure 1 gives a clue to the identity of one of the shocks. As previously noted, the CPS question asks workers the industry they were last employed in, so that unemployed in the N sector have never worked in any industry. Shocks which draw workers out of the N sector unemployment pool are likely to be common to all sectors (sector specificity is implausible for workers who have not previously worked in any sector), leaving the labour force entry as the only candidate for N sector factor which accounts for 13.6% of the variation in unemployment.

Figure 1 – Net Flows Affecting Employment and Unemployment by Industry

Another characteristic of the flows in and out of unemployment by industry illustrated in Figure 1 (that is not present in the flows in and out of employment by industry) is that a worker can only enter a sectoral unemployment pool from employment in that sector, while their exit from the

---

2 The literature on flows is vast (e.g. Davis and Haltiwanger (1999) Davis, Haltiwanger and Schuh (1996) Greenaway, Upward and Wright (2002)) but we focusing on net rather than gross flows, and unemployment by industry.

3 Measurement errors between not in the labour force and unemployment (highlighted by Poterba and Summers 1986 and others) could also be reflected in our estimate of the N sector contribution.
sectoral unemployment pool can be to employment in any sector or not in the labour force. This asymmetry between flows in and out of sectoral unemployment pools (which will be greater the more intersectorally mobile is a sector’s labour force) means that the sectoral shocks we are picking up are more likely to be positive shocks to unemployment (i.e shocks which increase unemployment).

8) CONCLUSIONS

Our main finding is that sectoral shocks are important but not dominant in post-war US unemployment movements, accounting for around half of the overall variation. This estimate is very general, and we believe robust, as not tied to a particular theory of unemployment. As well as our main finding, there is evidence that the sectoral shocks to unemployment tend to be of higher frequency than common shocks, and concentrated in particular sectors. There are also different patterns for different periods, with common factors dominating during the rise in unemployment in the 1970s, and sectoral factors being more important in the subsequent period of growth when unemployment fell. Sectoral shocks seem to be particularly important when we consider the shocks that push workers into the unemployment pool.

Based on these findings, the overwhelming emphasis of macroeconomists on aggregate forces needs to be modified to fully understand the evolution of US unemployment. Sectoral shock explanations of unemployment have been out of favour after criticism of Lilien’s (1986) study, but our work, along with the studies of Norrbin and Schlagenhauf (1988), Forni and Lippi (1997), Forni and Reichlin (1998) suggest sectoral shocks must be an important part of any explanation of the post-war US economic experience.

Although our main aim was quantifying the relative contributions of the general class of macro and micro shocks, there were some clues found about the identities of the common and sectoral shocks driving unemployment. Further work with particular sectoral shock models is needed to more precisely identify the forces we have described which drive unemployment. Another area for future work is cross-country comparisons – comparing the contributions of structural shocks in the US with European and Japanese unemployment would be interesting.
REFERENCES


