MICRO VS MACRO EXPLANATIONS OF POST-WAR US UNEMPLOYMENT MOVEMENTS

Chris Heaton, Macquarie University

Paul Oslington, University of New South Wales

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

* Address for correspondence Paul Oslington, School of Business, University of New South Wales/ADFA, Northcott Drive, Canberra 2602, Australia. Email: p.oslington@adfa.edu.au or Web: http://www.unsw.adfa.edu.au/sbus/staff_cvs/about_paul_osling.html
From 30 Sept 2006 until 31 July 2007 Paul Oslington will be on sabbatical at Princeton. Correspondence during time should be sent to 44 Alexander St (Apartment C3), Princeton NJ 08540-5119, USA. Tel 609-924 2313. Email or poslingt@princeton.edu.
Earlier versions have been presented at University of New South Wales and Australian National University and we thank seminar participants for helpful comments and suggestions. We especially thank Randy Ilg of the Bureau of Labour Statistics for his prompt and helpful responses to many queries about the data.

Abstract

We consider the contribution of sectoral shocks to post-war US unemployment movements in a dynamic factor framework. Whereas previously published estimates of the contribution of sectoral shocks to unemployment relate to a particular theory of unemployment, our approach is sufficiently general to encompass almost any theory. We estimate our model in the frequency domain using data on unemployment rather than employment or output. Sectoral shocks are found to account for around half the movements in US unemployment. These shocks tend to be of higher frequency than the common shocks and concentrated in the service and manufacturing sectors. Shock frequencies, sectoral patterns and flows provide some clues to the identity of some of the shocks driving unemployment. In some periods, such as the rise in unemployment in the 1970s, common shocks were dominant, but sectoral shocks have been more important in recent years.

1) INTRODUCTION

The causes of unemployment have been a matter of longstanding dispute in economics. Many different theories of unemployment have been proposed, and disputes over policy at times have been acrimonious. Effective policy depends on understanding the causes of unemployment movements, and 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 unemployment models have remained aggregate or single sector, even as macroeconomics moved to ground models in individual behaviour (Layard, Nickell and Jackman (2005)). However, there are a variety of disaggregate or “micro” models which combine sectoral shocks with slow or incomplete propagation. 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) is 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. Others take a different approach to the shock generating mechanism, with demographic adjustment featuring in Matsuyama (1992) and informational asymmetries in Riordan and Staiger (1993). Robert Hall (2003; 2005) suggests a number of other possible sectoral shock models of unemployment. Any general equilibrium trade model with unemployment (e.g. Matusz (1996), Oslington (2005), Melitz and Cunat (2006)) is a sectoral model.

Empirically the usual approach has been to test particular models of sectoral shocks. Some of the above models have performed reasonably well, but the argument for sectoral models would be more convincing if sectoral models were tested against a wide selection of aggregate models, and indeed against wide selection of sectoral models. An alternative approach is to estimate the contribution of sectoral factors without specifying a particular sectoral shock or adjustment mechanism. The much cited study of Lilien (1982) attempted to do this, but his index of sectoral employment variation is problematic (e.g capturing different sectoral sensitivities to the business cycle rather than sectoral shocks - see Abraham and Katz (1986), Murphy and Topel (1987)), but the main problem is that the credibility of the estimates depends on the validity of the monetary macroeconomic model to which the sectoral variation index is added.

This paper considers the contribution of sectoral shocks to post war US unemployment movements in a general framework that encompasses all possible “micro” and “macro” models of unemployment. We deliberately avoid imposing economic structure, and do not estimate a particular sectoral model of unemployment. Instead, dynamic factor techniques (introduced by Geweke (1977) and Sargent and Sims (1977), and explained more fully below) allow us to consider the contribution sectoral models in general to post-WWII US unemployment movements.

Some other studies have measured the contribution of sectoral shocks to US macro variables using a variety of methodologies. Long and Plosser (1987) used factor analysis techniques on output for sub-sectors of manufacturing from 1948 to 1981 to assess the importance of sectoral shocks. Norrbin and Schlagenhauf (1988) decomposed 1954 to 1980 US output movements into aggregate, sectoral 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.

Unlike previous work on sectoral shocks, we focus directly on unemployment rather than output or employment movements. There are several reasons for this. Firstly, 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)). Secondly, 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. Thirdly, using unemployment data focuses attention on the shocks that affect workers who remain unemployed, who are of most policy concern. Also, our study considers all sectors, including services and the public sector, rather than just sub-sectors of manufacturing, and a longer time series than existing work.

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 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 and allows comparability with other studies of sources of output and employment fluctuations.

The appendix illustrates the data for an example month and movements over the sample period.

---

[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

The empirical model is very general, encompassing almost all existing theories of unemployment. We want to avoid the problem of estimates of the contribution of sectoral shocks depending on the validity of a particular theory of unemployment or the business cycle.

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

(1) $$u_t = \sum_{j=0}^{\infty}\left(\lambda_j c_{t-j} + \varphi_j s_{t-j}\right)$$

where u_t is a px1 vector of weakly stationary sectoral contributions to unemployment.

c_t is a kx1 vector of common shocks where k is the number of common components.

λ_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, and

φ_j is a sequence of pxp diagonal matrices of coefficients capturing the effect of shocks originating in sectors on own and other sectors at all time lags.

Summing these sectoral contributions gives the aggregate unemployment rate:

(2) $$U_t = w' u_t$$

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 $z_t' = \left(c_t' \quad s_t'\right)$. We assume that $E\left(z_t\right) = 0$ and $E\left(z_t z_{t-j}'\right)$ 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, the Wold moving average representation is:

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

where Λ_j is a p×k matrix of moving average coefficients for the common component,

Ψ_j is a p×p diagonal matrix of moving average coefficients for the sectoral component, and all elements of the k×1 vector x_t and p×1 vector y_t are zero mean, unit variance, independent random variables.

The autocovariance function of u_t is

$$\text{(3)} \qquad \Gamma_u(r) = \sum_{j=0}^{\infty} \Lambda_j \Lambda_{j-r}' + \Psi_j \Psi_{j-r}' \qquad r = 0, 1, 2, \ldots$$

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

$$\text{(4)} \qquad F(\omega) = \sum_{v=-\infty}^{\infty} \sum_{j=0}^{\infty} \Lambda_j \Lambda_{j-v}' e^{-iv\omega} + \sum_{v=-\infty}^{\infty} \sum_{j=0}^{\infty} \Psi_j \Psi_{j-v}' e^{-iv\omega}$$

$$= \widetilde{\Lambda}(\omega)\widetilde{\Lambda}(\omega)^* + \widetilde{\Psi}(\omega)\widetilde{\Psi}(\omega)^* \qquad \omega = 0,\ldots,\pi$$

where $\widetilde{\Lambda}(\omega)$ and $\widetilde{\Psi}(\omega)$ are the Fourier transforms of Λ_j and Ψ_j respectively and * signifies the complex conjugate transpose.

4) ESTIMATION

Given n observations on u_t, the discrete Fourier transform of u the (n+1)/2 harmonic frequencies is

$$\text{(5)} \qquad \widetilde{u}(\omega) = n^{-\frac{1}{2}} \sum_{t=1}^{n} u_t e^{-i\omega t} \qquad \omega = 0,\ldots,\pi$$

From this, the periodogram ordinates are

(6) $$I(\omega) = \tilde{u}(\omega)\tilde{u}(\omega)^{*} \qquad \omega = 0,\ldots,\pi$$

The domain of I(ω) is divided into m non-overlapping sub-intervals and the spectral density on each sub-interval is estimated as

(7) $$S_m = \frac{1}{N}\sum_{j=1}^{N} I(\omega_{p,i})$$

where $\omega_{m,i}$, i = 1,…,N are the frequencies contained in sub-interval m. Assuming that x_t and y_t are Gaussian, S_m has a multivariate complex Gaussian distribution. Thus, the log-likelihood is

(8) $$\ln L = -\left(\ln\left|F_m(\omega)\right| + \mathrm{tr}\left(S_m F_m(\omega)^{-1}\right)\right)$$

where $F_m(\omega)$ is the spectrum in frequency band m. Under the factor model we have

(9) $$F_m(\omega) = \tilde{\Lambda}_m(\omega)\tilde{\Lambda}_m(\omega)^{*} + \tilde{\Psi}_m(\omega)\tilde{\Psi}_m(\omega)^{*}$$

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 generalisation to complex valued matrices of the EM algorithm constructed for static factor models by Rubin and Thayer (1982). This has the advantages of being relatively simple to code and of having robust, albeit possibly slow, convergence (Dempster, Laird and Rubin (1977)).

The discrete Fourier transform of the data yielded 330 periodogram ordinates between 0 and π. These were divided into five frequency bands and the factor model fitted. 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 χ^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

Frequencies	Ordinates	Cycles per year	Likelihood Ratio Statistics CV at .05 is 91.67 — 1 factor model $\chi^2(71)$
0 - 0.2π	1:66	0 - 1.2	77.8
0.2π - 0.4π	67:132	1.2 - 2.4	49.9
0.4 π -0.6 π	133:198	2.4 - 3.6	56.0
0.6π - 0.8 π	199:264	3.6 - 4.8	26.9
0.8 π - π	265:330	4.8 - 6	47.6

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

$$\frac{w'\left(\sum_{j=1}^{p}\underline{\tilde{\Lambda}}_j\underline{\tilde{\Lambda}}_j^*\right)w}{w'\left(\sum_{j=1}^{p}S_j\right)w} \tag{10}$$

where $\underline{\tilde{\Lambda}}_j$ is the maximum likelihood estimate of $\tilde{\Lambda}_j$.

5) RESULTS

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

Cycles pa	Common %	Sectoral %	Total %
0-1.2	35	2	37
1.2-2.4	4	6	10
2.4-3.6	2	11	13
3.6-4.8	4	14	18
4.8-6	5	16	21
Total %	51	49	100

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

Sector	Contribution %	Volatility
AG	1.9	0.7
MIN	1.3	3.3
MAN	9.6	0.6
CON	4.6	0.7
TRANS UT	1.7	0.2
TRADE	7.1	0.3
FIN	0.7	0.1
SERV	5.9	0.2
PUB	2.6	0.6
N	13.6	
Total %	49.0	

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 mostly strong growth from 1984 to end of our sample in 2002. Again we tested the goodness of the sub-period models, and Table 5 indicates the single common factor specification was not rejected for any sub-period.

Table 5 - Goodness of fit tests for factor models of sub-periods

		Likelihood Ratio Statistics CV at .05 is 91.67		
Frequencies	Cycles Pa	1 factor $\chi^2(71)$ Jan48 –Dec69	1 factor $\chi^2(71)$ Jan70 –Dec83	1 factor $\chi^2(71)$ Jan84 –Dec02
0 - 0.33π	0-2	70.46	78.36	62.47
0.33π - 0.66π	2-4	45.04	44.7	34.94
0.66 π - π	4-6	37.1	38.52	38.34 H

H denotes a Heywood case where one of the factors equals one of the variables – here the N sector contribution to unemployment. The asymptotic distribution of the likelihood statistic is not known, however Geweke and Singleton (1980) suggest a likelihood ratio test will not wrongly fail to reject the null hypothesis in these circumstances.

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

Cycles pa	Common %	Sectoral %	Total %	Common %	Sectoral %	Total %	Common %	Sectoral %	Total %
	Jan48 –Dec69			Jan70 –Dec83			Jan84 –Dec02		
0-2	37	5	42	51	4	55	23	8	31
2-4	5	13	18	8	13	21	6	24	30
4-6	17	24	40	5	19	24	0	38	38
Total %	59	41	100	64	36	100	30	70	100

The sectoral contributions for the sub-periods are given in Table 7. The sectors contributing most in the last 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

Sector	Contribution %		
	Jan48 –Dec69	Jan70 –Dec83	Jan84 –Dec02
AG	2	1	2
MIN	2	0	0
MAN	10	8	7
CON	4	3	7
TRANS UT	2	1	2
TRADE	5	5	13
FIN	0	1	2
SERV	4	3	13
PUB	1	1	5
N	11	13	19
Total %	41	36	70

7) WHAT MIGHT THE SHOCKS BE?

The main aim of our paper is to characterise the shocks driving unemployment, to guide further investigation using structural models. Existing work and some clues from our study suggest that candidate shocks for the common factor are:

- Technological change which affects all sectors.
- Effective demand variations.
- Institutional changes affecting the whole economy.
- Macroeconomic policy.

Candidate shocks for the sectoral factors are:

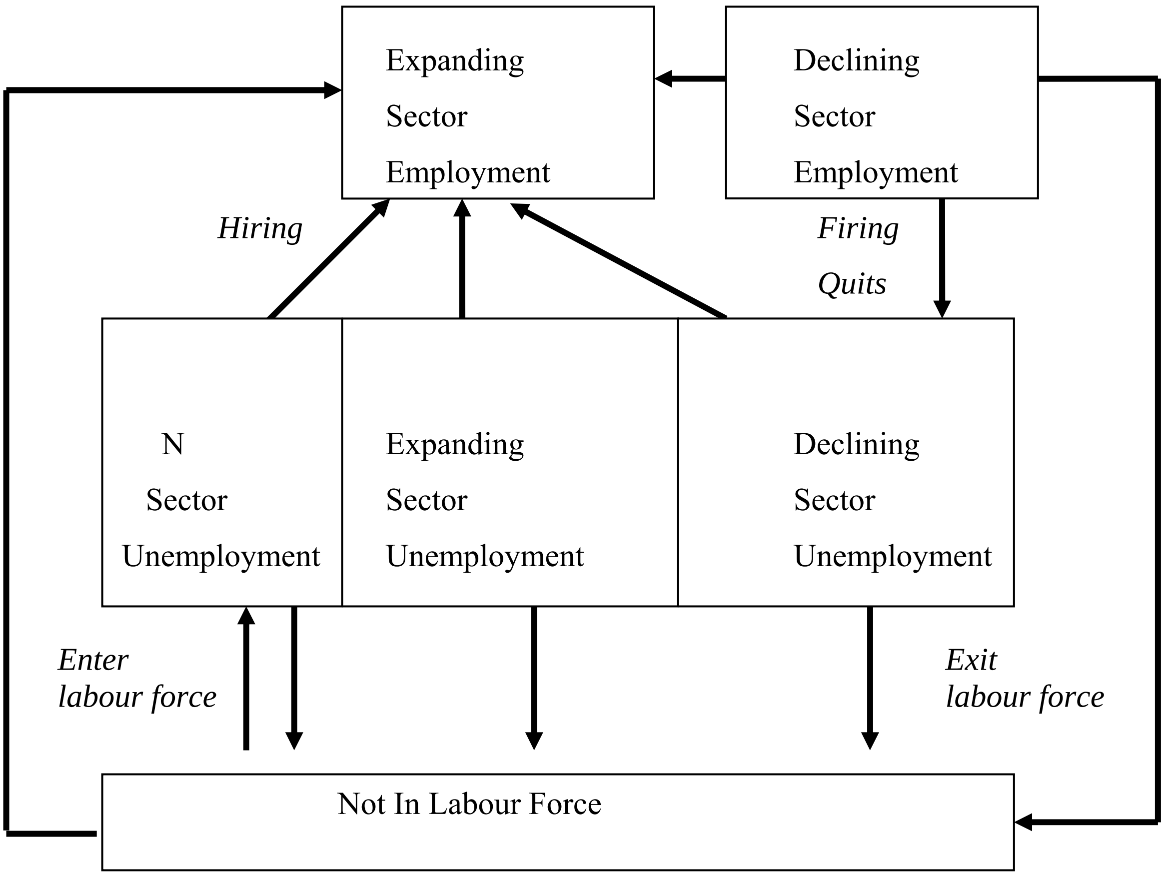
- Technological change which is specific to a sector, including new products.
- Changes in the pattern of demand across sectors.
- Institutional changes affecting particular sectors.
- Microeconomic policy.
- Trade changes, reflected in relative world commodity prices.

Do any of our factors looks 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.

Figure 1 – Net Flows Affecting Employment and Unemployment by Industry



The particular pattern of unemployment by industry net flows illustrated in figure 1 gives a clue to the identity of one of the shocks[2]. 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. This suggests the N sector factor we estimate is labour force entry. The reason is that 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[3].

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 sectoral unemployment pool can be to employment in any sector or they may leave the labour force. This asymmetry means that the sectoral shocks we are picking up are more likely to be shocks which increase unemployment, and the asymmetry will be greater the more intersectorally mobile is a sector's labour force.

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 it is 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.

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, and their close

---

[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.

association with real business cycle calibration methods. Our work, along with a number of recent studies (especially 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. Our work, in contrast to these studies has used unemployment data, so focuses on shocks that leaves workers in the unemployment pool. Sectoral shocks to unemployment are particularly important for these workers.

Although our main aim was quantifying the contribution of various types of 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.

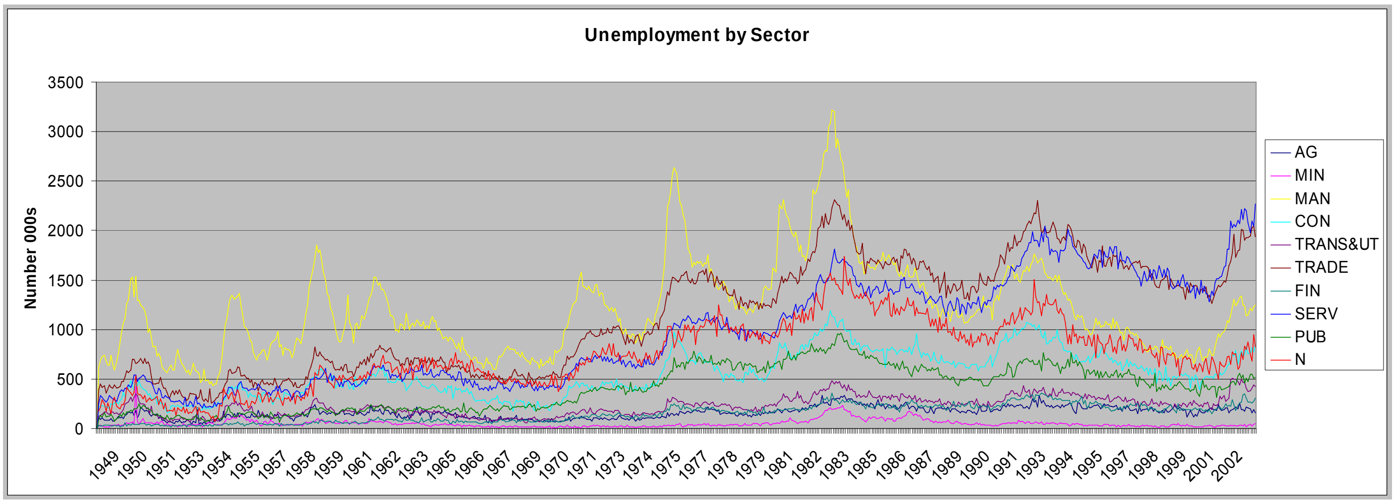
APPENDIX – DATA

The table below illustrates the data for an example year 1999. Note the wide variations in the unemployment rates between sectors from 2.9% for mining to 7.1% for construction.

Illustration - Data for 1999

	AG	MIN	MAN	CON	TU	TRADE	FIN	SERV	PUB	N	TOTAL
Unemployed Persons (000s)	190	16	890	635	295	1656	442	1816	420	569	6929
Employed Persons (000s)	3399	530	20835	8302	9182	26777	8297	46393	5738	n/a	129453
Proportion of Employment	2.6%	0.4%	16.1%	6.4%	7.1%	20.7%	6.4%	35.8%	4.4%	n/a	100%
Unemployment Rate	5.3%	2.9%	4.1%	7.1%	3.1%	5.8%	5.0%	3.8%	6.8%	n/a	5.1%
Contribution to Unemployment	0.1%	0.1%	0.7%	0.5%	0.2%	1.2%	0.3%	1.4%	0.3%	0.4%	5.1%

Movements in unemployment by industry over the period 1948-2002.



REFERENCES

Abraham, K. C. and L. F. Katz (1986). “Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances.” *Journal of Political Economy* 94: 507-22.

Crespo, R. (2005). *Total Factor Productivity: An Unobserved Components Approach*, Bristol Economics Discussion Papers UK.

Comin, D. and S. Mulani (2006). “Diverging Trends in Aggregate and Firm Volatility.” *Review of Economics and Statistics* 88(2): 374-83.

Davis, S. J. and J. Haltiwanger (1999). "Gross Job Flows" in *Handbook of Labor Economics Volume 3b* edited by O. Ashenfelter and D. Card. Amsterdam, North-Holland**:** 2711-805.

Davis, S. J., J. Haltiwanger and S. Schuh (1996). *Job Creation and Destruction* Mass, MIT Press.

Dempster, A. P., N. M. Laird and D. B. Rubin (1977). “Maximum Likelihood from Incomplete Data Via the Em Algorithm.” *Journal of the Royal Statistical Society - Series B* 39(1): 1-38.

Engle, R. and M. Watson (1981). “A One-Factor Multivariate Time Series Model of Metropolitan Wage Rates.” *Journal of the American Statistical Association* 76(376): 774-81.

Forni, M. and M. Lippi (1997). *Aggregation and the Microfoundations of Dynamic Macroeconomics* Oxford, Clarendon Press.

Forni, M. and L. Reichlin (1998). “Let's Get Real: A Factor Analytical Approach to Disaggregated Business Cycle Dynamics.” *Review of Economic Studies* 65: 453-73.

Geweke, J. (1977). "Dynamic Factor Analysis of Economic Time Series" in *Latent Variables in Socioeconomic Models* edited by D. Aigner and A. S. Goldberger. Amsterdam, North Holland.

Geweke, J. and K. J. Singleton (1980). “Interpreting the Likelihood Ratio Statistic in Factor Models When Sample Size Is Small.” *Journal of the American Statistical Association* 75: 133-7.

Greenaway, D., R. Upward and P. Wright (2002). "Sectoral Transformation and Labour Market Flows" in *Trade, Investment, Migration and Labour Market Adjustment* edited by D. Greenaway, R. Upward and K. Wakelin. New York, Palgrave Macmillan**:** 93-114.

Hall, R. E. (1999). "Labor-Market Frictions and Employment Fluctuations" in *Handbook of Macroeconomics Volume 1b* edited by J. B. Taylor and M. Woodford. Amsterdam, North-Holland**:** 1137-70.

Hall, R. E. (2003). “Modern Theory of Unemployment Fluctuations: Empirics and Policy Applications.” *American Economic Review* 93(2): 145-50.

Hall, R. E. (2005). "Job Loss, Job Finding, and Unemployment in the U.S. Economy over the Past Fifty Years" in *National Bureau of Economic Research Macroeconomics Annual* edited by. Chicago, National Bureau of Economic Research.

Layard, R., S. Nickell and R. Jackman (2005). *Unemployment: Macroeconomic Performance and the Labour Market* Second edition. Oxford, Oxford University Press.

Lilien, D. M. (1982). “Sectoral Shifts and Cyclical Unemployment.” *Journal of Political Economy* 90(4): 777-93.

Ljungqvist, L. and T. J. Sargent (1998). “The European Unemployment Dilemma.” *Journal of Political Economy* 106(3): 514-50.

Long, J. and C. I. Plosser (1983). “Real Business Cycles.” *Journal of Political Economy* 91:39-69.

Long, J. and C. I. Plosser (1987). “Sectoral Vs Aggregate Shocks in the Business Cycle.” *American Economic Review* 77: 333-6.

Lucas, R. E. and E. C. Prescott (1974). “Equilibrium Search and Unemployment.” *Journal of Economic Theory* 7: 188-209.

Matsuyama, K. (1992). “A Simple Model of Sectoral Adjustment.” *Review of Economic Studies* 59: 375-88.

Matusz, S. (1996). “International Trade, the Division of Labour and Unemployment.” *International Economic Review* 77(2): 71-84.

Melitz, M. J. and A. Cunat (2006). “Volatility, Labor Market Flexibility and the Pattern of Comparative Advantage.” Manuscript.

Murphy, K. M. and R. H. Topel (1987). "The Evolution of Unemployment in the United States: 1968-1985" in *Nber Macroeconomics Annual* edited by S. Fischer. Mass, MIT Press**:** 11-58.

Norrbin, S. C. and D. E. Schlagenhauf (1988). “An Inquiry into the Sources of Macroeconomic Fluctuations.” *Journal of Monetary Economics* 22(1): 43-70.

Oslington, P. (2005). “Unemployment and Trade Liberalisation.” *World Economy* (Aug): 1139-55.

Poterba, J. M. and L. H. Summers (1986). “Reporting Errors and Labor Market Dynamics.” *Econometrica* 54(6): 1319-38.

Riordan, M. H. and R. W. Staiger (1993). “Sectoral Shocks and Structural Unemployment.” *International Economic Review* 34(3): 611-29.

Rogerson, R. (1987). “An Equilibrium Model of Sectoral Reallocation.” *Journal of Political Economy* 95(4): 824-34.

Rubin, D. B. and D. T. Thayer (1982). “EM Algorithms for ML Factor Analysis.” *Psychometrika* 47(1): 69-76.

Sargent, T. and C. Sims (1977). "Business Cycle Modeling without Pretending to Have Too Much a Priori Theory" in *New Methods in Business Cycle Research* edited by C. Sims. Minneapolis, Federal Reserve Bank.

Shumway, R. H. and D. S. Stoffer (1982). “An Approach to Time Series Smoothing and Forecasting Using the Em Algorithm.” *Journal of Time Series Analysis* 3: 253–64.

Stock, J. H. and M. W. Watson (1999). "Business Cycle Fluctuations in Us Macroeconomic Time Series" in *Handbook of Macroeconomics Volume 1a* edited by J. B. Taylor and M. Woodford. Amsterdam, North-Holland**:** 3-64.

Watson, M. W. and R. Engle (1983). “Alternative Algorithms for Estimation of Dynamic Mimic, Factor, and Time Varying Coefficient Regression Models.” *Journal of Econometrics* 23: 385-400.