How Much Unemployment is Structural?

by

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Abstract

Knowledge of the extent to which the unemployment rate is driven by sectoral shocks is important for the development of appropriate unemployment theory and policy. In this paper we estimate a non-parametric dynamic factor model using Australian data and decompose the variance of changes in unemployment into macroeconomic and sectoral components. We find that, while sectoral shocks contribute to unemployment, they are not dominant, accounting for around 21 per cent of the variance of changes in the aggregate unemployment rate. Furthermore, we find that this contribution is concentrated at the higher frequencies. Sectoral shocks make almost no contribution to longer-run changes in unemployment.

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

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1) INTRODUCTION

Structural unemployment is much discussed in the academic and popular literature on unemployment, but there is little consensus about how much of the rise in unemployment across the OECD since the early 1970s can be attributed to structural factors. This lack of consensus continues partly because of the many and sometimes imprecise ways in which the structural contribution to unemployment has been defined and measured. It is an issue of considerable importance for public policy because if structural factors are dominant, more emphasis should be placed on industrial and labour market adjustment policy, trade policy and other microeconomic policies in the fight against unemployment, rather than macroeconomic policy.

A comprehensive and influential study of the issue was Layard, Nickell and Jackman (1991). Drawing partly on the earlier work of Jackman and Roper (1987), they defined the structural contribution to unemployment in terms of mismatch between the supply and demand for particular types of labour. Using data for several countries for as long as the series were available, they looked for changes in various measures of mismatch which might have explained the rise in unemployment. While remaining agnostic on the proportion of the stock of unemployment that was structural, they found their measures of mismatch had not changed much over the period in which OECD unemployment had risen, and therefore could not have been responsible for the large change in unemployment that we have observed over the last twenty five years.

To investigate the issue further there are two alternative strategies. The first is to specify a particular model which generates structural unemployment and then estimate and/or test it. This strategy has been pursued by many researchers, including Lilien (1982), who added an index of structural change (the dispersion of growth rates of employment by industry) to a macroeconomic model where variations in unemployment are driven by unanticipated monetary shocks. Subsequent studies using similar methods have included Mills, Pelloni and Zervoyianni (1995), Mills, Pelloni and Zervoyianni (1996) and Groenewold and Hagger (1998). A problem with this strategy is that there are as many estimates of the contribution of structural change to variations in unemployment as there are macroeconomic models, and the validity of the estimates depends on the validity of the macroeconomic model in which the structural change parameter is included.

An alternative strategy, to be pursued in this paper, is to seek an estimate of the contribution of structural shocks to variations in the unemployment rate which is not tied to any particular theoretical model of unemployment. Pursuing this strategy means we are not testing a particular model of structural unemployment, but rather assessing the explanatory power of the general class of explanations of unemployment which focus on structural shocks. Other studies by Rowthorn and Wells (1987) and Gregory and Greenhalgh (1996) have estimated the contribution of structural change in the form of deindustrialisation in ways which are less model specific than most of the literature, although their particular methods are quite different to the present paper.

The aim of this paper is to estimate the proportion of the variation in unemployment since the 1970s that is due to structural shocks. The particular dimension of structure to be considered will be industry structure, and so the question will be the proportion of unemployment that is accounted for by industry specific shocks, as against shocks common to all industries. We define a common shock to unemployment as one which affects all industries, not necessarily equally or contemporaneously. Sectoral shocks are then by definition mutually orthogonal and orthogonal to the common shocks. The aggregate unemployment rate is then a linear function of these shocks and the only other assumptions we make are that the shocks either follow Gaussian processes or satisfy sufficient regularity conditions that a central limit theorem applies to their discrete Fourier transforms (see, for example, Brillinger (1981) or Hannan (1970). Given our definition of shocks, the distributional assumptions and the assumption of linearity are sufficient to allow estimation of the shocks as latent stochastic processes. Furthermore, we use a non-parametric frequency domain estimation method which obviates the need to specify a lag structure for the model. The attraction of our approach is the mildness of the assumptions. The validity of our measure does not depend on the validity of any particular theory of the unemployment rate. Rather, it provides some empirical evidence which can aid in the construction of theory and the choice of policy.

The econometric techniques employed in this paper were proposed by Geweke (1977) and used by Sargent and Sims (1977) and Geweke and Singleton (1981). A more popular methodology for dynamic factor analysis is to employ the Kalman Filter in the EM algorithm to estimate the model in the time domain, as proposed by Watson and Engle (1983) and Shumway and Stoffer (1982). However, this approach was not used since it requires the specification of a lag structure. A further advantage of the

Geweke approach is that the frequency decomposition of the variance reveals important information which would be obscured in the time domain.

2) DATA

In order to estimate the proportion of variation in unemployment that is due to industry specific shocks we need data on unemployment by industry. These data are collected as part of the standard ILO labour force survey carried out by many countries. As part of the labour force survey, the unemployed are asked if they have worked full time for more than two weeks in the last two years, and if so the industry is recorded. If not, they are recorded as not attached to an industry. These unattached unemployed could be new entrants to the labour force, long term unemployed who have worked but not in the last two years, or unemployed who have only previously worked part time in an industry in the last two years. While not a perfect measure of unemployment specific to industries, it is the best available.

Our data are monthly from the Australian labour force survey for the period February 1978 to July 1994[1]. The data are differenced and rescaled to a zero mean, but not seasonally adjusted. Similar UK data are not available since the labour force survey has been only carried out annually for most of the period, and the claimant count series gives no information about the industry an unemployed person last worked in.

Unemployed workers are classified into 17 ANZSIC (Australia and New Zealand Standard Industry Classification) 1 digit industries. More disaggregated data may provide more detail on the precise source of shocks. However some aggregation of industries will reduce the number of parameters to be estimated while still allowing the common component to be estimated. We have chosen to aggregate to give the following 9 industry sectors[2] (abbreviated names bracketed):

Sector 1 - Agriculture, Fishing, Hunting and Services to Agriculture (AG)

Sector 2 - Manufacturing and Metal Products (MAN)

Sector 3 – Construction (CON)

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[1] The first stage of our work is with Australian data from Australian Bureau of Statistics *The Labour Force Australia* (various issues) Catalogue no. 6203. In 1994 the classifications were changed substantially so data since then has not been used to avoid comparability problems. We would ideally have liked to have data back another few years to cover the early 1970s, but while the data were collected they are unfortunately not available from the Australian Bureau of Statistics.

[2] The structure of the model, and some minor experimentation, lead us to believe that our results are robust to changes in the level and composition of aggregation.

Sector 4 - Wholesale Trade, Retail Trade, Transport and Storage (TRADE)

Sector 5 - Finance, Property and Building Services (FIN)

Sector 6 - Public Admin and Defence, Rec, Community, Personal and Other Services (SERV)

Sector 7 – Mining (MIN)

Sector 8 - Electricity, Gas and Water and Communications (UTIL)

Sector 9 - No Industry (N)

To give an idea of the orders of magnitude of the data, Table 1 gives observations for May 1994. A sectoral unemployment rate is defined as unemployed persons in the sector divided by the sum of unemployed and employed persons in the sector. A sectoral contribution to unemployment is unemployed persons in the sector divided by total unemployed and employed persons in all sectors. The sectoral contributions thus sum to the overall rate of unemployment. We will be working with the sectoral contributions rather than sectoral unemployment rates so as to reduce possible measurement errors associated with the sectoral employed persons data series. Note the wide variations in the unemployment rates between sectors in Table 1; from 2.7% for financial property and building services, to 6.7% for manufacturing. Of the workers not attached to any industry, roughly half are new entrants, one third have worked but not in the last two years, and about one sixth have only worked part time in an industry in the last two years.

Table 1 - Labour Force Survey Data for May 1994

	AG	MAN	CON	TRADE	FIN	SERV	MIN	UTIL	N	TOTAL
Unemployed Persons (000s)	25	79	38	117	28	87	6	8	424	804
Employed Persons (000s)	405	1101	559	2054	1022	2434	88	124	n/a	7663
Unemployment Rate	5.8%	6.7%	6.4%	5.4%	2.7%	3.5%	6.4%	6.1%	n/a	9.5%
Contribution to Unemployment	0.3%	0.9%	0.4%	1.4%	0.3%	1.0%	0.1%	0.1%	5.0%	9.5%

Figure 1 (presented in the appendix) plots the sectoral unemployment rates over the sample period. Note the differences in the variability between sectoral rates and how often the rankings of sectors changes.

3) MODEL

The model is very simple and general, for the reasons given in the introduction. It is assumed that the sectoral contributions to unemployment are driven by a stochastic process that is unique to that sector and by a process that is common to all sectors so

(1) $u_t = \lambda * m_t + \varphi * \varepsilon_t$

where u_t is a px1 vector of sectoral contributions to unemployment, m_t is a kx1 vector of common components (k<p), ε_t is a px1 vector of sector-specific components, λ and φ are matrices of coefficients, and * denotes convolution such that

(2) $\lambda * m_t = \sum_{j=-\infty}^{\infty} \lambda_s m_{t-s}$

The sectoral contributions to unemployment are unemployed persons in a particular industry divided by the total labour force.

Summing these sectoral contributions gives the aggregate unemployment rate:

(3) $U_t = w' u_t$

where w is a px1 vector of 1s. Note that we do not need a vector of weights of each sector because we are working with sectoral contributions to the aggregate unemployment rate rather than sectoral unemployment rates.

It is assumed that the vectors m_t and ε_t are zero-mean, mutually independent, covariance stationary, strictly indeterministic variables. Thus, following Wold (1954) they have moving average representations such that

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

where

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

Ψ is a p×p 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.

Given the properties of x and y, the variance of the overall unemployment rate is

$$(5)\quad \mathrm{VAR}(U_t) = w'\left\{\sum_{j=0}^{\infty}\left(\Lambda_j\Lambda_j' + \Psi_j\Psi_j'\right)\right\}w$$

Thus, the variance is decomposed into a component due to common effects $w'\sum_{j=0}^{\infty}\Lambda_j\Lambda_j'w$ and a component due to sector-specific effects $w'\sum_{j=0}^{\infty}\Psi_j\Psi_j'w$.

4) ESTIMATION

The estimation procedure used in this paper is that proposed by Geweke (1977). This may be viewed as the classical static factor analysis of Jöreskog (1967) and Lawley and Maxwell (1971) generalised to factorise a spectral density matrix rather than a covariance matrix. While this generalisation presents some issues for the calculus needed, the computational details are identical to the static case except that the matrices are now complex rather than real, and the matrix transpose used is the complex conjugate transpose. With this in mind Jöreskog (1967) and Lawley and Maxwell (1971) provide an excellent account of the details of the computational methodology used.

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

$$(6)\qquad \begin{aligned} F(\omega) &= \sum_{v=-\infty}^{\infty}\ \sum_{j=0}^{\infty}\Lambda_j\Lambda_{j-v}'e^{-iv\omega} + \sum_{v=-\infty}^{\infty}\ \sum_{j=0}^{\infty}\Psi_j\Psi_{j-v}'e^{-iv\omega} \\ &= \sum_{j=-\infty}^{\infty}\Lambda_j e^{-ij\omega}\sum_{v=-\infty}^{\infty}\Lambda_{j-v}'e^{i(j-v)\omega} + \sum_{j=-\infty}^{\infty}\Psi_j e^{-ij\omega}\sum_{v=-\infty}^{\infty}\Psi_{j-v}'e^{i(j-v)\omega} \\ &= \sum_{j=-\infty}^{\infty}\Lambda_j e^{-ij\omega}\sum_{r=-\infty}^{\infty}\left(\Lambda_r e^{ir\omega}\right)^H + \sum_{j=-\infty}^{\infty}\Psi_j e^{-ij\omega}\sum_{r=-\infty}^{\infty}\left(\Psi_r e^{ir\omega}\right)^H \\ &= \tilde{\Lambda}(\omega)\tilde{\Lambda}(\omega)^H + \tilde{\Psi}(\omega)\tilde{\Psi}(\omega)^H \end{aligned}$$

where $\tilde{\Lambda}(\omega)$ and $\tilde{\Psi}(\omega)$ are the Fourier transforms of Λ_j and Ψ_j respectively and ^{H} signifies the complex conjugate transpose. The Fourier transform of the macroeconomic unemployment rate is given by

(7) $F_U(\omega) = w'F(\omega)w$.

Thus, the factor decomposition of the autocovariance function implies an analogous factor decomposition of the spectrum of u (and U).

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

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

From this, the periodogram ordinates are

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

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

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

where $\omega_{m,i}$, i = 1,…,N are the frequencies contained in sub-interval m, and the model fitted to each frequency band. Assuming either that x_t and y_t are normal or that sufficient conditions are satisfied for a central limit theorem to apply to $\tilde{u}(\omega)$, S_m has a multivariate complex normal distribution. Since the periodogram ordinates are asymptotically independent, the log-likelihood is

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

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

(12) $$F_m(\omega) = \tilde{\Lambda}_m(\omega)\tilde{\Lambda}_m(\omega)^H + \tilde{\Psi}_m(\omega)\tilde{\Psi}_m(\omega)^H$$

The estimates of $\tilde{\Lambda}_m(\omega)$ and $\tilde{\Psi}_m(\omega)$ are the values of $\underline{\tilde{\Lambda}}_m$ and $\underline{\tilde{\Psi}}_m$ which minimise the function

$$(13)\qquad \Phi(S_m, \underline{\tilde{\Lambda}}_m, \underline{\tilde{\Psi}}_m) = \ln\left|\underline{\tilde{\Lambda}}_m \underline{\tilde{\Lambda}}_m{}^H + \underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right| + \mathrm{tr}\left[S_m\left(\underline{\tilde{\Lambda}}_m \underline{\tilde{\Lambda}}_m{}^H + \underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{-1}\right]$$

It should be noted that the likelihood is a real-valued function of complex-valued parameters and is therefore not holomorphic. Nevertherless, stationary points may be found by differentiating with respect to the real and imaginary parts of the parameters separately. Jöreskog (1967) shows that[3], given $\underline{\tilde{\Psi}}_m$ the conditional maximum likelihood estimate of $\underline{\tilde{\Lambda}}_m$ is

$$(14)\qquad \underline{\tilde{\Lambda}}_m = \left(\underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{\frac{1}{2}} \Omega(\Theta - I)^{\frac{1}{2}}$$

where Θ is the diagonal matrix with the largest k eigenvalues of $\left(\underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{\frac{1}{2}} S_m \left(\underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{\frac{1}{2}}$ arranged in descending order, and Ω is a matrix that has the corresponding eigenvectors as columns. Thus, this parameter may be concentrated out of the likelihood function yielding

$$(15)\qquad \phi(\underline{\tilde{\Psi}}_m) = -\ln \prod_{i=1}^{p-k} \theta_{k+i} + \sum_{i=1}^{p-k} \theta_{k+i} - (p-k)$$

where the θ_i are the p-k smallest eigenvalues of $\left(\underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{\frac{1}{2}} S_m \left(\underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{\frac{1}{2}}$. The first partial derivative of ϕ is

$$(16)\qquad \frac{\partial\phi}{\partial\underline{\tilde{\Psi}}_m} = \mathrm{diag}\left[\left(\underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{-1}\left(\underline{\tilde{\Lambda}}_m \underline{\tilde{\Lambda}}_m{}^H + \underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H - S_m\right)\left(\underline{\tilde{\Psi}}_m \underline{\tilde{\Psi}}_m{}^H\right)^{-1}\right]$$

Geweke (1977) follows Jöreskog (1967) in proposing that equation (15) be maximised by utilising equations (14) and (16) in the Fletcher Powell (1963) algorithm. It is worth noting that this algorithm is based on a quadratic approximation and forms an estimate of a symmetric hessian matrix in order to determine the direction of each step in the algorithm. However, the fact that the likelihood is not holomorphic implies that the true hessian is not symmetric. This raises questions about the computational efficiency of gradient methods in this context. Nonetheless, the estimated hessian is guaranteed to be positive definite so that convergence may be expected. In practice it was found that, with some experimentation with starting values, convergence was achieved in reasonable time. A further problem that is created by the non-symmetric hessian is that it is unclear how meaningful standard error estimates may

[3] Jöreskog (1967) shows this for the static factor model in which all parameters are real. However, if the complex conjugate transpose is read in place of the standard matrix transpose and the 'derivative' is defined as $\frac{\partial\phi}{\partial\underline{\tilde{\Lambda}}_m} = \frac{\partial\phi}{\partial \mathrm{Re}(\underline{\tilde{\Lambda}}_m)} + i\frac{\partial\phi}{\partial \mathrm{Im}(\underline{\tilde{\Lambda}}_m)}$, his results hold in the complex case also.

be derived. However, since the principal aim of this research is measurement rather than hypothesis testing, this is not considered to be a major drawback.

5) RESULTS

The Fourier transform of the 198 observations yielded 99 periodogram ordinates between 0 and π. These were divided into four frequency bands (0-1.5, 1.5-3.0, 3.0-4.5, 4.5-6.0 cycles per year) 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. It was initially assumed that each frequency band is driven by a single common factor. Factor representations were tested using a likelihood ratio test, with Bartlett's (1951) finite-sample multiplying factor applied. The degrees of freedom of the test are $\frac{1}{2}\left[(p-k)^2-(p+k)\right]$. If the hypothesis of a single common factor is rejected by the likelihood ratio test, then another common factor is added and the model re-estimated, and so on. At a significance level of 5% the restriction that there is one common factor was accepted in all frequency bands except the lowest. In this band, the hypothesis of two common factors was accepted. Test statistics for the goodness of fit of the models are presented below in Table 2.

Table 2 - Goodness of fit tests for factor models

			Likelihood Ratio Statistics	
Frequencies	Ordinates	Cycles per year	1 factor $\chi^2(27)$ CV = 40.11	2 factors χ^2 (19) CV = 30.14
0.01π-0.24π	1 – 24	0 - 1.5	52.57	23.12 H
0.25π-0.51π	25 – 49	1.5 - 3	32.8	-
0.52π-0.75π	50 – 74	3 - 4.5	25.66	-
0.76π- π	75 – 99	4.5 - 6	31.77 H	-

Cases in which the maximum likelihood solution involves a zero element in $\underline{\tilde{\Psi}}_p \underline{\tilde{\Psi}}_p{}^H$ (often referred to as a Heywood case in classical factor analysis) are marked with an H in Table 2. These may be interpreted as situations in which one of the factors is equal to one of the variables. In both cases, it is the 'no industry' sector which is equal to the common factor, a situation which is reasonable given that one of the factors is the non-sector specific component of unemployment. In Heywood cases, the asymptotic distribution of the likelihood ratio statistic is unknown. However, Monte Carlo simulations by Geweke and Singleton (1980) suggest that using the likelihood ratio test in such situations will lead to the factor model being rejected too often, so it is unlikely that we are incorrectly accepting the model.

For those frequency bands in which the single factor model was accepted, $\tilde{\Lambda}$ is uniquely identified (up to a scalar constant). In these cases, the single factor is assumed to be a macroeconomic factor common to all sectors[4]. For the two-factor model estimated for the lowest frequency band, $\tilde{\Lambda}$ is unidentified in the sense that any unitary transformation of $\tilde{\Lambda}$ will result in an alternative but equally valid[5] two-factor representation of the data. While the decomposition of the variance of unemployment into components due to the common and sector-specific factors is independent of any transformation of $\tilde{\Lambda}$, the interpretation of the second common factor as a macroeconomic component may not be valid. In particular, it is possible that the second common factor is common to only a subset of the sectors and is therefore not truly macroeconomic. For example, the weather could be a factor which affects both agriculture and construction, but not the other sectors. In this case, the second column of $\tilde{\Lambda}$ would have zeros in all rows except those corresponding to agriculture and construction. In order to prevent mis-interpretation of the common factor vector, it is necessary to impose identifying restrictions on $\tilde{\Lambda}$. Our argument is as follows. The 'no sector' sector is unique in that it is not tied to any particular industry but rather consists of the long-term unemployed and those who have never worked. Accordingly, if the second factor is a factor common to only a subset of sectors then it must have a zero loading for the 'no sector' sector. Following Howe (1955) this single zero restriction is identifying in our case. Imposing this restriction, taking the absolute value of the second row of $\tilde{\Lambda}$, and weighting by the contributions to unemployment from Table 1 gives the following:

AG	5.6626	
MAN	5.2781	
CON		6.7123
TRADE	2.5667	
FIN	3.0299	
SERV	1.5603	
MIN	2.3322	

[4] This assumption is entirely reasonable. Visual inspection of the sectoral contributions to unemployment reveals clear evidence of a component common to all sectors. This is particularly obvious during the recessions of the early 1980s and 1990s.

[5] The alternative representation is equally valid in the sense that it also maximises the likelihood function.

UTIL	1.5897

Since there is no obvious sign of the factor being relevant to only a subset of the sectors, we conclude that the second factor is in fact macroeconomic[6].

The proportion of the variance of the overall unemployment rate that is accounted for by aggregate forces is estimated as

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

It is found that 79 per cent of the variance of the overall rate of unemployment is accounted for by macroeconomic shocks, with the remaining 21 per cent being accounted for by sector-specific shocks. Table 3 shows how the total variance of unemployment is distributed across the frequency bands and the proportion of the variance that is accounted for by the common and sector-specific factors.

Table 3 – Variance decomposition of overall unemployment rate

		Cycles pa			
	0 - 1.5	1.5 - 3	3 - 4.5	4.5 – 6	Total
Common	31%	27%	11%	10%	79%
Sectoral	1%	4%	12%	4%	21%
Total	32%	31%	23%	14%	100%

The common component to unemployment is concentrated at the lower frequencies. Thus, the extent to which changes in aggregate unemployment are driven by sectoral influences depends greatly on the

[6] If the second factor was not a macroeconomic factor then one would expect the coefficients to be close to zero for all but a couple of sectors which share similar characteristics. This does not appear to be the case. As explained previously, meaningful standard error estimates cannot be easily derived since the likelihood is not holomorphic.

frequency of fluctuations that one is interested in. It is interesting that the higher frequencies also have a high concentration of aggregate fluctuations[7].

The breakdown by sector of the 21 percent sectoral contribution to the variance of unemployment is shown in table 4. Note that the largest contributors (besides not attached to any industry) are manufacturing, wholesale/retail trade/transport and storage, and services. This is consistent with a structural shift from manufacturing to services since the 1970s. The large effect from the not attached to any industry sector, reflects the inability of the other sectors to absorb new labour force entrants and the long term unemployed.

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

	Sector									
	AG	MAN	CON	TRADE	FIN	SERV	MIN	UTIL	N	Total
Contribution	1.77%	2.67%	1.13%	2.11%	0.48%	1.97%	0.11%	0.11%	10.36%	21%

6) CONCLUSIONS

Our results suggest that common or macroeconomic shocks have been the dominant influence on the evolution of Australian unemployment over the period 1978-1994, accounting for 79% of the variation in unemployment. Like Layard, Nickell and Jackman (1991) we conclude that structural change has not been the main culprit in the rise in unemployment over the last two decades. Our conclusions are inconsistent with the claims often made in the popular press, and also with the results of some prominent studies in the literature, including Lilien (1982) who attributed up to half of the variation in US unemployment over the period to changes in industry structure. The advantage of our methodology is that

[7] It is possible that a common measurement error contributes to this, suggested by the frequency being the same as our measurement interval. The common measurement error is that in some months the sample will include too many unemployed people and sometimes too few. However, there are also sector-specific sampling errors (some weeks the sample will contain too many manufacturing people in the sample, etc). Since the ABS labour force survey covers something like 60,000 households, the measurement error should be quite small. In any case, the error will only be correlated over 2 months (the ABS keeps part of the sample each month so they can measure labour force flows), which is more than 6 cycles per annum. This would be aliased by the highest frequency band only. Since this only contributes 13% to the variance of aggregate unemployment, the impact of measurement error should be negligible.

it is a formal approach based on very general assumptions. Since previously published research in this area has typically been based on less formal methods, or on methods which rely on the validity of a particular *a priori* theory of unemployment, these results contribute to our understanding of the importance of structural shocks to changes in unemployment.

An interesting aspect of the sectoral shocks we identified was that they tended to be fairly high frequency while the aggregate shocks dominate the lower frequencies. The contribution of sectoral shocks at higher frequencies was 46 per cent, compared to 21 per cent overall. In the low frequency band, shocks to aggregate unemployment are almost entirely macroeconomic in origin. Forni and Reichlin (1998) found that sectoral shocks in US output also tended to be high frequency and common shocks low frequency. Our finding that the structural shocks make very little contribution to the low frequencies suggests that the labour market is in fact quite good at clearing relative imbalances in unemployment conditions quickly. It is the common shocks to unemployment which generate the long term changes.

A further conclusion is that within the sectoral contributions, manufacturing, services, and public sectors are the largest components. This partly reflects the sizes of these sectors, but is also consistent with the widely noted shift from manufacturing to services in OECD countries combined with reductions in public sector employment since the 1970s.

Overall, theories of structural unemployment do have an important role to play in the explanation of the overall unemployment rate, but this role is limited. The research presented in this paper gives reason to be skeptical of claims that all our unemployment is structural or that the whole focus of fight against unemployment should be microeconomic policies.

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Appendix

Figure 1 - Unemployment Rates by Sector