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The Contribution of Structural Shocks to Australian Unemployment*

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In this paper dynamic factor analysis techniques are used to decompose changes in unemployment into industry sectoral and common components. Sectoral shocks are important, but the dominant causes of variation in unemployment are common to all industries. This is particularly the case for low-frequency fluctuations in unemployment. The pattern of the estimated sectoral shocks reflects the well-documented shift of employment from agriculture and manufacturing to services, and we find no evidence that microeconomic reform has contributed greatly to unemployment.

I Introduction

Structural unemployment has been widely discussed in the academic and popular literatures, but there is little consensus about how much of the rise in unemployment since the 1970s can be attributed to structural factors. The issue is of considerable importance for public policy because, if structural factors are dominant, emphasis should be placed on industry, labour market, and other microeconomic policies rather than macroeconomic policies in fighting unemployment (Productivity Commission 1997, 1998).

Most Australian work on structural unemployment has used techniques from an important paper by Lilien (1982) on the contribution of industry sectoral shocks to USA unemployment movements.[1] Lilien constructed an index of the volatility of employment growth rates across 11 USA industries for the period 1948–1980, and added the index as a variable to a macroeconomic model in which changes in unemployment are driven by unanticipated monetary shocks. Finding the volatility index variable was statistically significant, he decomposed unemployment movements into a macroeconomic component (attributable to the unanticipated monetary shocks) and a sectoral component (attributable to the volatility index). This decomposition also yielded a natural rate of unemployment series, where the

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[1] Lilien (1982) and much of the related literature focuses on the industry sectoral dimension of structure. There exist other dimensions of structure (e.g., occupation, age, gender) which might also be considered. The methods used in this paper can be extended to analyse several dimensions of structure simultaneously. However, while the Australian Labour Market Survey should yield the cross-tabulated unemployment data that we would need to extend our study to other dimensions of structure, the Australian Bureau of Statistics was unable to supply such data after lengthy negotiations. Accordingly, we follow most of the literature in considering only the industry sectoral dimension of structure.

natural rate was defined as the rate of unemployment that would have prevailed had the unanticipated monetary shock been zero. On the basis of this work, Lilien concluded that 'as much as half of the variance of unemployment over the post war period can be attributed to fluctuations in the natural rate brought about by the slow adjustment of labour to shifts of employment between sectors of the economy' (Lilien 1982, p. 778). There has been considerable scepticism about Lilien's high estimate of the contribution of structural shocks to unemployment movements, but his work and conclusions remain influential.

The first application of these techniques to Australian unemployment was Trivedi and Baker (1985). Their study added a Lilien index to various macroeconomic models and, using data for 1970–1983 found that 'most of the observed increase in unemployment has been due to non-frictional and non-structural factors … Proximate causes of unemployment are real award wages and insufficient demand' (Trivedi & Baker 1985, p. 642). Hoque and Inder (1991) regressed the proportion of unemployment in particular industries on a Lilien index and the participation rate for the period 1976–1987. Their overall conclusions, in contrast to Trivedi and Baker, were 'certainly in favour of a structural unemployment hypothesis' (Hoque & Inder 1991, p. 629). More recently, controversy has been generated by Groenewold and Hagger's (1998) finding that most of the increase in Australian unemployment over the period 1979–1993 was due to increases in the natural rate coming from sectoral disturbances, and that aggregate influences played a negligible role (Groenewold & Hagger 1998, p. 25, 33).[2] This implied that 'it is to micropolicy that we should be looking, not macro-policy, if we wish to improve our unemployment record' (Groenewold & Hagger 1998, p. 31). Their work followed Lilien's original methods fairly closely, although with some variations in econometric technique, including an attempt to purge common components from the structural change index (see the discussions in Debelle & Lowe 1999 and Groenewold & Hagger 1999).

There are a number of fundamental problems with Lilien's methods of estimating the contribution of structural shocks to unemployment – with implications for the Australian studies. First, the volatility index may not be capturing sectoral shocks, but different sensitivities of sectors to shocks that are common to all sectors, as was pointed out by Abraham and Katz (1986). Second, even if the index is capturing sectoral shocks, there will be as many estimates of the contribution of structural change to unemployment as there are macroeconomic models to which the index can be added. The sensitivity of the estimates of the contribution of structural change is indicated by the divergent results from the Australian studies and attempts to apply Lilien's methods to other countries.[3]

At a deeper level, we are unsatisfied with highly model-specific approaches to the measurement of structural unemployment when there is little consensus about the mechanisms generating structural unemployment, and certainly no single well accepted model.[4] In this paper we take a different approach to most of the existing literature and estimate the contribution of structural shocks to unemployment changes in a very general non-parametric framework that is consistent with almost any model of unemployment.

The aim of the paper is to estimate the proportion of changes in Australian unemployment since the 1970s due to industry specific shocks, as against shocks common to all industries. Both the industry specific components and the common components of unemployment will be modelled as latent stochastic processes, and estimated using dynamic factor analysis techniques. These techniques were introduced by Geweke (1977) and have been used to study interest rates (Singleton 1980), business cycles (Sargent & Sims 1977; Watson & Kraft, 1984; Forni & Reichlin 1998), and linkages between

[2] Some of the literature equates structural unemployment with the natural rate of unemployment. The most common definition of the natural rate in the macroeconomic literature is the rate of unemployment below which the actual rate cannot be forced by demand management policies. Structural unemployment is one of many reasons why the unemployment rate cannot be reduced, so in our view estimates of the natural rate are not particularly useful measures of structural unemployment, although they may indicate an upper bound.

[3] Results from the overseas studies using Lilien's methods vary widely. See for example Layard *et al.* (1991), Palley (1992), Mills *et al.* (1995) and Chapple *et al.* (1996).

[4] Some theoretical models do of course exist – including Rogerson (1987), Ljungqvist and Sargent (1998), Davidson and Matusz (2000).

countries' business cycles (Norrbin & Schlagenhauf 1996). Forni *et al.* (2000) have recently generalised the model and further developed the estimation techniques.

II Data

Most previous work on sectoral shocks has used employment data. We believe that unemployment data is more appropriate – if workers leave their job in one sector and are re-employed in another, then the structure of employment has changed, but structural unemployment has not. It is the workers who remain unemployed who are of concern to policy makers.

Data on unemployment by industry are collected as part of the Australian Bureau of Statistics Labour Force Survey.[5] While not perfect, it is the best available measure of structural unemployment. In the survey unemployed persons are asked if they have worked full time for more than 2 weeks in the last 2 years. If so, this industry is recorded. If not, they are recorded as not attached to an industry. Approximately one-half of these unattached unemployed are new entrants to the labour force, approximately one third are long-term unemployed who have worked but not in the last 2 years, and approximately one-sixth are unattached because they have only previously worked part time in the last 2 years.

Our data are monthly for the period February 1978 to July 1994. In 1994 the industry classifications were changed substantially so to avoid comparability problems, data since 1994 have not been used. Data from the early 1970s would have shed light on this crucial period in the evolution of Australian unemployment, but they are not available from the Australian Bureau of Statistics in comparable and useable form. Seasonal adjustment has been carried out using the X-11 procedure in SPSS (SPPS, Chicago, IL, USA), and the data have been differenced and rescaled to a zero mean. Plots of the adjusted and unadjusted aggregate unemployment data, their spectra and the spectra of their first differences appear in Figure 1. The shapes of the spectra are typical of macroeconomic series with most of the density concentrated at the lower frequencies (Granger 1966). As always, differencing shifts the density towards the higher frequencies. The X-11 procedure has successfully removed the seasonal component without otherwise greatly affecting the spectral shape of the series.

Unemployed workers in the data set are classified into 17 ANZSIC 1 digit industries. We have aggregated to yield nine industry sectors which we will subsequently refer to by the following abbreviations:

AG –	Agriculture, fishing, hunting and services to agriculture
MAN –	Manufacturing and metal products
CON –	Construction
TRADE –	Wholesale trade, retail trade, transport and storage
FIN –	Finance, property and building services
SERV –	Public administration and defence, community, personal and other services
MIN –	Mining
UTIL –	Electricity, gas and water communications
N –	No industry

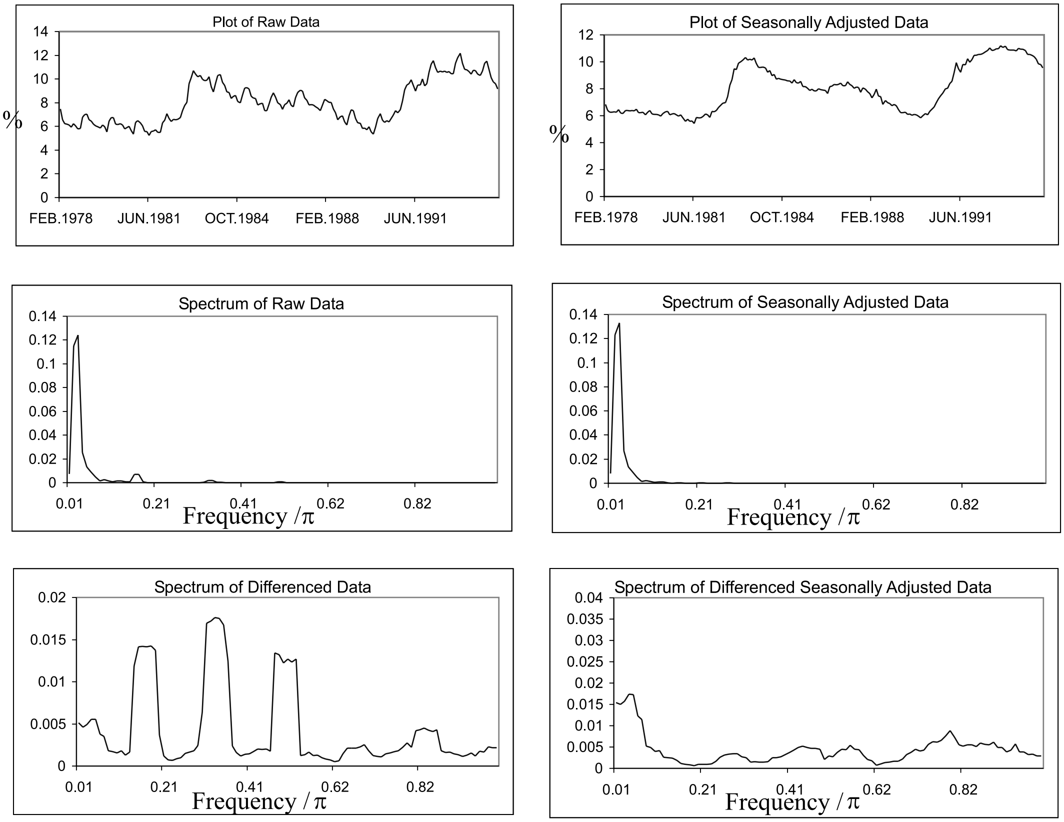
Less aggregation might yield more detailed results. However, aggregation will not affect our main result, as common components are still common when sectors are aggregated. Furthermore, aggregation reduces the number of parameters that need to be estimated, so some aggregation is desirable. However, identification problems will be encountered if the level of aggregation is too great. The number of sectors we have chosen is a compromise between these considerations and is similar to other studies of sectoral unemployment. Some minor experimentation leads us to believe that our results are reasonably robust to changes in the level of aggregation.

To give an idea of the orders of magnitude of the data, observations for May 1994 are presented in Table 1. A sectoral unemployment rate is defined as the number of unemployed persons in the sector divided by the sum of the numbers of unemployed and employed persons in the sector. A sectoral contribution to unemployment is the number of unemployed persons in the sector divided by the total number unemployed and employed persons in all sectors. The sectoral contributions (including 'no industry') thus sum to the overall rate of unemployment. We have chosen to work with sectoral contributions rather than sectoral unemployment rates to avoid

[5] The source of the data is *The Labour Force Australia* Australian Bureau of Statistics Catalogue no. 6203.

FIGURE 1

Plots of the raw and seasonally adjusted aggregate unemployment data and spectra of the seasonally adjusted data in levels and first differences*



* *The estimates are average-smoothed periodograms. For the spectra of the levels data the width of the frequency band used in the averaging is three frequencies, and for the spectra of the differenced data seven frequencies. Note that a frequency of 0.01π–0.33π corresponds to 0–2 cycles per year, 0.34π–0.66π is 2–4 cycles per year, and 0.67π–π is 4–6 cycles per year.*

TABLE 1

Labour Force Survey Data for May 1994

	AG	MAN	CON	TRADE	FIN	SERV	MIN	UTIL	N	Total
Unemployed persons (000 s)	25	79	38	117	28	87	6	8	424	804
Employed persons (000 s)	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

AG, agriculture, fishing, hunting and services to agriculture; CON, construction; FIN, finance, property and building services; MAN, manufacturing and metal products; MIN, mining; N, no industry; SERV, public administration and defence, community, personal and other services, TRADE; wholesale trade, retail trade, transport and storage; UTIL, electricity, gas and water communications.

problems of weighting sectors over the sample period and to reduce possible measurement errors associated with the sectoral employed persons data series that we would have had to use to calculate the sectoral unemployment rates. Note the wide variations in the unemployment rates between sectors in Table 1; from 2.7 per cent for financial property and building services to 6.7 per cent for manufacturing.

III Model

In view of the wide variation in results and problems with the some of the existing model-specific studies, our aim is to use the most general model possible. We assume that the unemployment rate in each sector is a linear function of a vector process that is common to all sectors and a scalar process that is sector specific. We therefore have

$$u_t = \sum_{j=0}^{\infty} \lambda_j m_{t-j} + \epsilon_t \qquad (1)$$

where u_t is a $p \times 1$ vector of sectoral contributions to unemployment for which we have data (p is the number of sectors); m_t is a $k \times 1$ vector of stochastic processes representing the k unobserved common components to unemployment movements. We are allowing more than one common component to unemployment movements although the number must be less than the number of sectors, that us $k < p$. λ_j where $j = 0, \ldots, \infty$ is a sequence of $p \times k$ matrices indicating the sensitivities of each of the p sectors to the k common components at all possible lags;[6] and ϵ_t is a $p \times 1$ matrix of stochastic processes representing the unobserved sectoral components of unemployment movements.

Summing the sectoral contributions in Equation (1) gives the aggregate unemployment rate:

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

where w is a $p \times 1$ unit vector. Recall that there is no need for sectoral weights because we have chosen to work with sectoral contributions to the unemployment rate rather than sectoral unemployment rates. It must be emphasised that Equation (1) is not a conventional regression equation. There are no explanatory variables in the usual sense; m_t and ϵ_t are latent or unobservable processes that we will estimate indirectly. What we are doing is decomposing the observed unemployment movements into unobservable common and sectoral components without the use of proxy variables such as the Lilien index.

We assume that the elements of the stacked vector (m_t) are zero mean, mutually independent, covariance stationary and strictly indeterministic variables. They will be zero mean because our data have been scaled to a zero mean. Mutual independence is a consequence of our definitions of sectoral and common – if the shocks are not independent they cannot be truly sector-specific. Covariance stationarity is reasonable given that the data are differenced.

Under our assumptions, following Wold (1954), m_t and ϵ_t have moving average representations such that

$$u_t = \sum_{j=0}^{\infty} \Lambda_j x_{t-j} + \sum_{j=0}^{\infty} \Psi_j y_{t-j} \qquad (3)$$

where the Λ_js are $p \times k$ matrices of moving average coefficients for the common component, the ψ_js are $p \times p$ diagonal matrices of moving average coefficients for the sectoral component, all elements of the $k \times 1$ vector x_t and $p \times 1$ vector y_t are zero mean, unit variance, independent random variables, and $E(x_t x'_{t-j}) = 0$, $E(y_t y'_{t-j}) = 0$ for all $j \neq 0$ and $E(x_t y'_{t-j}) = 0$ for all j.

Given the properties of x_t and y_t, the variance of the overall unemployment rate is

$$VAR(U_t) = w' \left\{ \sum_{j=0}^{\infty} \left(\Lambda_j \Lambda'_j + \Psi_j \Psi'_j \right) \right\} w \qquad (4)$$

Thus, the variance of changes in the overall unemployment rate can be decomposed into a component due to common influences $w' \sum_{j=0}^{\infty} \Lambda_j \Lambda'_j w$ and a component due to sector-specific influences $w' \sum_{j=0}^{\infty} \psi_j \psi'_j w$.

IV Estimation

Direct estimation of Equation (3) is complicated by the lack of a finite lag structure. Rather than imposing an arbitrary lag structure on the model, we follow Geweke (1977) and transform the model to the frequency domain. The frequency domain representation of a time series model is equivalent to the time domain representation,

[6] The λ_j matrices are important because one of the criticisms of the Lilien method was that it does not distinguish different sensitivities of sectors to common shocks from the sectoral shocks. These different sensitivities are isolated in our λ_j matrices.

although less familiar to most economists. In the frequency domain the stochastic processes are represented as combinations of sine/cosine waves of different frequencies and amplitudes rather than as shocks with lag structures.[7] The main attraction of working in the frequency domain is that we avoid having to specify lag structures for the unobserved stochastic processes that we are trying to estimate – economic theory gives little guidance on this matter. A further advantage is that the frequency domain representation yields a natural decomposition into long-run (low frequency) and short-run (high frequency) fluctuations. It must be emphasised that the frequency domain representation is simply a more convenient way to write the above model – it imposes no assumptions on the model that have not already been listed.

The frequency domain representation is derived by taking the Fourier transform of the autocovariance function of equation (3). Geweke (1977) shows that this yields

$$F(\omega) = \tilde{\Lambda}(\omega)\tilde{\Lambda}(\omega)^{H} + \tilde{\Psi}(\omega)\tilde{\Psi}(\omega)^{H} \qquad (5)$$

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 then given by

$$F_U(\omega) = w'F(\omega)w. \qquad (6)$$

Thus, the variance decomposition of Equation (4) implies an analogous decomposition of the spectrum of U.

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

$$\tilde{u}(\omega) = n^{-\frac{1}{2}}\sum_{t=1}^{n} u_t e^{-i\omega t} \quad \omega = 0, \ldots, \pi \qquad (7)$$

From this, the periodogram ordinates are

$$I(\omega) = \tilde{u}(\omega)\tilde{u}(\omega)^{H} \quad \omega = 0, \ldots, \pi \qquad (8)$$

The domain of $I(\omega)$ is divided into m non-overlapping subintervals and the spectral density on each subinterval is estimated as

$$S_m = \frac{1}{N}\sum_{j=1}^{N} I(\omega_{m,i}) \qquad (9)$$

where $\omega_{m,i}, i = 1, \ldots, N$ are the frequencies contained in subinterval m. Assuming that x_t and y_t are Gaussian, Geweke (1977) exploits the asymptotic independence of the transformed observations of u_t to develop a maximum likelihood estimate of the model parameters for each band of frequencies used in Equation (9). The reader is referred to this source for details of the estimation technique. Geweke's approach may be viewed as a generalisation of classical static factor analysis to complex-valued matrices. Accordingly, Jöreskog (1967) and Lawley and Maxwell (1971) are also useful references for readers interested in the details of estimation.

We have divided the transformed vectors of sectoral unemployment contributions into three frequency bands (0–2, 2–4 and 4–6 cycles per year) and fitted the model to each band. An advantage of the technique that we are using is that we can conduct likelihood ratio tests of the dimension of the common factor vector m_t in each frequency band (i.e., the value of k). The distribution of the test statistic is chi-squared with $\frac{1}{2}[(p - k)^2 - (p + k)]$ degrees of freedom. As the periodogram ordinates are asymptotically independent, we can also construct a joint test by summing the test statistics for each frequency band. We begin by testing the null hypothesis of a single common component against the alternative that there is more than one common component. We can then add common components if necessary. The relevant test statistics are in Table 2.

The joint hypothesis that there is one common factor in all frequency bands was not rejected at the 5 per cent significance level, and in the high and medium frequency bands the independent tests did not reject the null hypothesis that there is one common factor in the frequency band. In the lowest frequency band where the null was rejected, the rejection was marginal. The probability of rejecting at least one correct null hypothesis in a sequence of three independent hypothesis tests with nominal significance levels of 5 per cent is over 14 per cent. Given this, and the fact that the joint test accepts the null, we consider a model with one common factor (i.e. $k = 1$) to be appropriate.

Given the parameter estimates, the proportion of the variance of changes in the unemployment

[7] Granger and Watson (1984) and Granger (1987) provide an overview of frequency domain (or spectral) methods.

TABLE 2
Tests of the single common component model

Frequencies	Cycles per year	Likelihood Ratio Statistics for Independent Tests
0.01π–0.33π	0–2	40.96
0.34π–0.66π	2–4	23.94 H[8]
0.67π–π	4–6	30.63 H
		Likelihood ratio statistic for joint test = 95.53
Critical value for independent tests $\chi^2(27) = 40.11$		Critical value for joint test $\chi^2(81) = 103.01$

rate that is due to common shocks in frequency band j may be estimated as[9]

$$\frac{w'\underline{\tilde{\Lambda}}_j\underline{\tilde{\Lambda}}_j^H w}{w' S_j w} \tag{10}$$

and the overall proportion estimated by the sum of this statistic over the three frequency bands.

V Results

Table 3 shows estimates of the proportion of the variance of unemployment shocks accounted for by the common and sector-specific components and the distribution of the variance across the frequency bands.

TABLE 3
Variance decomposition of shocks to the aggregate unemployment rate

	Cycles per year			
	0–2	2–4	4–6	Total
Common (%)	31	11	18	60
Sectoral (%)	8	13	19	40
Total (%)	39	24	37	100

Our main result is that 60 per cent of the variation in the rate of unemployment is accounted for by the common shocks, and the remaining 40 per cent by sector-specific shocks.[10] It is important to remember we are decomposing changes in the unemployment rate, and not levels – we are saying that 60 per cent of the variation since the early 1970s is accounted for by common shocks, not that 60 per cent of the current stock of unemployment is due to common shocks. Also recall that a shock is regarded as industry specific if it only affects one industry and common if it affects two or more industries – not necessarily with the same intensity.[11]

The largest single component of the variance is in the lowest frequency band (0–2 cycles per year) as is usual for macroeconomic time series, even when differenced. What is interesting is the overwhelming dominance of common factors at low frequencies – they account for approximately 80 per cent of the variance (i.e., 31 per cent divided by 39 per cent in Table 3). This is consistent with the finding of Forni and Reichlin

[8] 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 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 failing to reject the null.

[9] The underscore denotes an estimated parameter.

[10] 'No industry' was counted as a sector so that the sectoral contributions would sum to the overall unemployment rate and because we did not want to throw away these data (the 'no industry' is a mixture of new entrants to the labour force, long-term unemployed and unemployed who have only ever worked part time). However, it is debatable whether it is appropriate to count it as part of the sectoral contribution to unemployment movements. If the 'no industry' is excluded common shocks would account for approximately 63 per cent of the variation and sectoral shocks 37 per cent.

[11] It might be thought that the estimated common factor may be an artifact induced by the X-11 seasonal adjustment procedure. However, this is not the case. In earlier work (Heaton & Oslington, 1999) we estimated the model without seasonally adjusting the data and the estimated common component accounted for 80 per cent of the variance. This suggests that seasonality is a predominantly common component which has been removed by the adjustment procedure.

TABLE 4
The contribution of each sector to the variance of the aggregate unemployment rate

	Sector									
	AG	MAN	CON	TRADE	FIN	SERV	MIN	UTIL	N	Total
Contribution (%)	6.1	9.0	3.9	7.3	1.5	6.7	0.4	0.4	4.7	40
Weighted contribution	20.3	10.0	9.8	5.2	5.0	6.7	4.0	4.0	0.9	

AG, agriculture, fishing, hunting and services to agriculture; CON, construction; FIN, finance, property and building services; MAN, manufacturing and metal products; MIN, mining; N, no industry; SERV, public administration and defence, community, personal and other services, TRADE; wholesale trade, retail trade, transport and storage; UTIL, electricity, gas and water communications.

(1998) that the common shocks to USA output were of lower frequency than the sector specific shocks. Our finding that most of the low frequency variations common shocks is significant because the low frequency variations in unemployment are likely to be of most policy interest. It is also interesting that such a large proportion of the variance is in the highest frequency band. An inspection of Figure 1 suggests that this is primarily due to the differencing of the data. However, it is also likely that some portion of this apparent variation is measurement error. This is not necessarily a problem. The high-frequency component of unemployment is essentially frictional and might be regarded as being of lesser interest – both because it has a smaller welfare cost than the low frequency component, and because it is generally regarded as being beyond the reach of discretionary policy. Furthermore, if we exclude the highest frequency band from the analysis it makes little difference to the overall decomposition of variance into common and sectoral components. Accordingly, we view the issue of measurement error in the highest frequency band as being relatively unimportant.

The contributions of the sectoral shocks to the variance of the aggregate unemployment rate are shown in Table 4. The largest contributors to unemployment movements have been the manufacturing, trade, services and agricultural sectors. This is not surprising as these are the largest sectors, in terms of their contributions to the unemployment rate. To show the impact of each sector relative to its size, weighted contributions to aggregate unemployment are calculated in Table 4 (the weights are the number of unemployed persons in each industry from Table 2). The weighted contributions also suggest that the agricultural, manufacturing, construction, trade and service sectors have been the most turbulent, although the rankings have changed – trade appears to be less volatile and agriculture far more so after weighting by size. This finding is consistent with the well documented structural shift from agriculture and manufacturing to services in recent years.

Our findings shed light on the widespread view that microeconomic reform has contributed greatly to the rise in Australian unemployment. The issue was previously considered by the Productivity Commission (1997), who constructed a Lilien index for Australia and also used input-output methods to decompose changes in employment by industry into trade, technological change, final demand and other effects. Based on the decompositions, and equating microeconomic reform with productivity improvements, they concluded that 'microeconomic reform has probably influenced employment in those industries where significant microeconomic reform has taken place' (p. 15). However, our analysis by sector in Table 4 does not reveal unusually large contributions to unemployment from sectors identified by Productivity Commission (1997, p. 2) as sectors where microeconomic reform has been concentrated – namely utilities, transport and communication and finance. There are two issues that must be considered when comparing our findings with those of the Commission. Firstly, we are looking at unemployment rather than employment changes, so while employment may have contracted in those industries, the displaced workers are not being picked up in our unemployment data and thus seem to have been reasonably successful in finding jobs in other sectors. The possibility that the displaced workers have left the labour force cannot be ruled out. Secondly, while our findings do not support the proposition that microeconomic reform in specific industries has had a major influence on unemployment in Australia, microeconomic reforms which affect all industries would be part of the common component of unemployment movements and thus not picked up in Table 4.

VI Conclusions

Our results suggest that common shocks rather than sector-specific shocks have been the major influence on the evolution of Australian unemployment over the period 1978–1994, accounting for over half of the variation in the unemployment rate. Sectoral shocks are important, but not dominant. Of particular significance is our finding that at the lowest frequencies approximately 80 per cent of the variance of changes to unemployment are caused by factors common to all industries. High-frequency fluctuations in unemployment are beyond the reach of discretionary policy because of the lags involved in observation and policy implementation. In any case, being short-lived, the high-frequency fluctuations in unemployment might be viewed as being of lesser importance. It is the low-frequency fluctuations that create the greatest social welfare costs and these are predominantly the result of factors which are common across sectors. Also of interest are the sources of the sectoral shocks, in particular the evidence of aggregate unemployment being affected by the shift from agriculture and manufacturing to services, and the lack of evidence of a large contribution to unemployment from sectors which have experienced significant microeconomic reform.

Our work has used unemployment rather than employment data and different techniques to the existing research, and so our study is not comparable in detail to previous Australian research. Our results, though, suggest that sectoral shocks are more important than was found by Trivedi and Baker (1985) or Productivity Commission (1998). However, to the extent that microeconomic policy is industry-specific, our results are inconsistent with Groenewold and Hagger's conclusion (1998, p. 31) that microeconomic policy is likely to provide the best hope of improving our unemployment record.[12]

The objective of our work has been to quantify the contributions to unemployment of common and sectoral factors while remaining agnostic about the economic mechanisms represented by the factors. Many macroeconomists would see the common factor as representing aggregate demand shocks, but other possibilities include a technology shock that affects many sectors (e.g., computerisation), or some kind of common institutional shock (e.g., changes in minimum award wages or social security payments). Similarly the sectoral shocks could be sector specific technological change, or changes in demand at the sectoral level.

Due to the generality of the approach, we believe that our estimate of the contributions of common and sectoral shocks to unemployment is more reliable than those derived from the existing model-specific approaches. This does not mean however, that we reject modelling of the mechanisms behind structural unemployment. Quite the contrary, we hope that this information about the magnitude and characteristics of sectoral and common shocks will stimulate further work on the mechanisms generating unemployment, and appropriate remedies.

[12] In defence of Groenewold and Hagger, they point out their paper is applying Lilien methods to Australia in spite of a number of reservations about the techniques.

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