



# Micro vs macro explanations of post-war US unemployment movements

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## ABSTRACT

This paper considers contributions of industry-sectoral-micro shocks vs aggregate macro shocks. A dynamic factor model is estimated with maximum likelihood method in the frequency domain, and decomposes US unemployment movements into industry sectoral and common components. Sectoral shocks account for around half unemployment movements.

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## 1. Introduction

The causes of unemployment are a matter of longstanding debate in economics. Many different theories have been proposed, and disputes over policy at times have been acrimonious. Effective policy depends on understanding the causes of unemployment movements and a fundamental question is whether these causes are sector-specific or common to all sectors. If most shocks are aggregate then the traditional focus on “macro” models and policy is appropriate, but if sectoral shocks are more important then we need “micro” models and policy interventions which focus on the relevant sectors.

Most theoretical models of unemployment are highly aggregate single sector models (for instance [Layard, Nickell and Jackman \(2005\)](#)). However, there exist a variety of disaggregate or “micro” models in which sector-specific shocks drive unemployment movements. [Lucas and Prescott's \(1974\)](#) seminal paper showed how orthogonal product demand sectoral shocks and a search across spatially separated markets generate unemployment. [Rogerson \(1987\)](#) developed this further in a two period, two sector setting, and [Ljungqvist and Sargent's \(1998\)](#) influential ‘turbulence plus skill decay’ account of European unemployment is from this family of models. There are many possible shock generating mechanisms, such as demographic adjustment in [Matsuyama \(1992\)](#) and informational

asymmetries in [Riordan and Staiger \(1993\)](#). [Robert Hall \(2003, 2005\)](#) suggests further possible sectoral shock models of unemployment. Any general equilibrium trade model with unemployment (e.g. [Oslington, 2005](#)) is also a sectoral model of unemployment.

Empirically, the most common approach to identifying shocks to unemployment has been to test the restrictions implied by particular models of unemployment such as the ones above. An alternative empirical strategy is to estimate the contribution of sectoral factors while remaining agnostic about the particular sectoral shock or adjustment mechanism. The much cited study of [Lilien \(1982\)](#) attempted to do this by adding an index of the sectoral dispersion of the unemployment rate to a then standard macroeconomic model. [Abraham and Katz \(1986\)](#) criticised aspects of Lilien's methodology, but the main problem is that the estimate of the contribution of the sectoral shock term depends on the validity of the underlying macroeconomic model into which it is inserted.

This paper quantifies the contributions of sectoral and aggregate shocks to post-war US unemployment movements in a very general framework. It utilizes the frequency domain exact factor model of [Geweke \(1977\)](#) and [Sargent and Sims \(1977\)](#) to decompose the aggregate unemployment rate into a set of mutually orthogonal sector-specific and common shocks. The model is estimated by the maximum likelihood method. Our aim is not to test particular hypotheses, or confirm or repudiate any particular theoretical model of unemployment, but to provide evidence about the classes of models and policies – macro or micro – that researchers and policy makers should be focusing on. An alternative approach to maximum

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likelihood estimation of the exact factor model would be to use dynamic principal component techniques to estimate an approximate factor model which allows for a limited degree of cross-correlation between the sector-specific components. Forni, Hallin, Lippi and Reichlin (2000) and Forni, Hallin, Lippi and Reichlin (2004) study such a model. Consistency of the dynamic principal components estimator is proved in a setting in which the number of sectors goes to infinity with the number of observations. For our application, data with a sufficiently high degree of disaggregation for the dynamic principal component theory to be applicable were not available. For this reason, we consider likelihood estimation of the exact factor model, which assumes the sector-specific shocks to be cross-sectionally uncorrelated, to be the best choice of methodology. In the context of a time domain factor model, Doz, Giannone and Reichlin (2007) have shown that the maximum likelihood estimator is consistent in the presence of sector-specific cross-correlation in a setting with a large number of sectors. It seems likely that a similar result would hold in the frequency domain, which suggests that our approach may have some robustness to deviations from the exact factor model in some settings.

Some other studies have compared aggregate and sectoral shocks using broadly similar methodologies. Long and Plosser (1987) used factor analysis techniques on output for sub-sectors of US manufacturing from 1948 to 1981 to assess the importance of sectoral shocks. Norrbin and Schlagenhauf (1988) decomposed US output movements from 1954 to 1980 into aggregate, sectoral and regional components using the Engle–Watson DYMIC techniques (Watson and Engle, (1983)). Forni and Reichlin (1998) considered very finely disaggregated US manufacturing output for the period 1958–86 using their own dynamic factor techniques.

## 2. Data

Data on unemployment by industry sector are available from the US Bureau of Labour Statistics (BLS)<sup>1</sup>. 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. 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), Public Administration (PUB) and Not Attached (N)<sup>2</sup>. For each sector we define the sectoral contribution to the unemployment rate as the number of unemployed persons in the sector divided by the total labour force in all sectors<sup>3</sup>. Consequently, sectoral contributions sum to the aggregate unemployment rate.

The data are monthly for the period January 1948 to December 2002. We have chosen not to use data after 2002 because 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

<sup>1</sup> 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.

<sup>2</sup> Aggregation makes a difference to results. The greater the number of sectors, the less likely are shocks to be confined to a sector and hence the higher will be the estimated contribution of sectoral shocks to unemployment movements. Ten sectors is a natural level of aggregation in the data which allows comparison with other studies of sources of output and employment fluctuations. We have chosen to work with monthly data, but using quarterly or annual data would give more time for shocks originating in a sector to dissipate across the economy, meaning these shocks may be wrongly measured as aggregate shocks.

<sup>3</sup> We work with sectoral contributions to unemployment rather than sectoral unemployment rates to reduce possible measurement errors associated with the sectoral employed persons' data series.

existing data series at all levels of occupation and industry aggregation”. The series that we use have been seasonally adjusted by the BLS, and we have taken first differences and rescaled to a zero mean.

## 3. Model

Our empirical approach is based on the frequency domain exact factor model of Geweke (1977) and Sargent and Sims (1977). The joint spectrum of the sectoral contributions to unemployment is divided into a set of non-overlapping frequency bands, and the factor model is fitted to each band using the maximum likelihood method. We then use the model to construct estimates of the variance decomposition of the aggregate unemployment rate into sector-specific and common components in each frequency band. We now briefly outline some details of this approach.

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

$$u_t = \sum_{j=0}^{\infty} B_j c_{t-j} + s_t \quad (1)$$

where  $u_t$  is a  $p \times 1$  vector of sectoral contributions to unemployment;

$c_t$  is a  $k \times 1$  vector of weakly dependent, covariance stationary common shocks where  $k$  is the number of common components;  $B_j$  is a sequence of  $p \times k$  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  $p \times 1$  vector of weakly dependent, covariance stationary sector-specific shocks.

Summing these sectoral contributions gives the aggregate unemployment rate:

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

where  $w$  is a  $p \times 1$  unit vector.

We assume (i) orthogonality between the sector-specific and common components at all leads and lags, and (ii) cross-sectional orthogonality of the sector-specific components at all leads and lags. These assumptions correspond to our notion of a sector-specific shock as being unique to a particular sector, and are sufficient for statistical identification of the common component  $\sum_{j=0}^{\infty} B_j c_{t-j}$  and the idiosyncratic component  $s_t$  (see Theorem 1, Heaton and Solo (2004)). In applications of the factor model it is usually assumed that the factors are mutually uncorrelated and of unit variance, so that the factor loadings and factors are identified up to an orthogonal transformation. If sufficient restrictions on the factor loading matrices exist, then the factors may be uniquely identified (see Geweke and Singleton (1981)). However, the variance decomposition of unemployment that is implied by the factor model is invariant to non-singular transformations of the factors, so we do not need to impose restrictions of this type.

Since the common and sector-specific components are covariance stationary and weakly dependent, they have purely indeterministic Wold representations. Therefore, Eq. (1) may be written as

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

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

The autocovariance function of  $u_t$  is

$$\Gamma_u(r) = \sum_{j=0}^{\infty} (\Lambda_j \Lambda'_{j-r} + \Psi_j \Psi'_{j-r}) \quad r = 0, 1, 2, \dots \quad (3)$$

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

$$F(\omega) = \sum_{v=-\infty}^{\infty} \sum_{j=0}^{\infty} \Lambda_j \Lambda'_{j-v} e^{-iv\omega} + \sum_{v=-\infty}^{\infty} \sum_{j=0}^{\infty} \Psi_j \Psi'_{j-v} e^{-iv\omega} \quad (4)$$

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

where  $\tilde{\Lambda}(\omega)$  and  $\tilde{\Psi}(\omega)$  are the Fourier transforms of  $\Lambda_j$  and  $\Psi_j$  respectively and  $^H$  signifies the complex conjugate transpose. We divide the spectrum into a set of non-overlapping frequency bands, assume that the spectrum is constant within each band, and maximize the Gaussian likelihood function for each band.

#### 4. Results

The discrete Fourier transform of the data yielded 330 periodogram ordinates between 0 and  $\pi$ . These were divided into five frequency bands and the factor model fitted to each band. An advantage of the technique we are using is that we can test for the number of common factors in each frequency band, using a likelihood ratio test. The test statistic has a  $\chi^2$  distribution with  $(p-k)^2 - p$  degrees of freedom. Test statistics for the goodness of fit of the model are presented in Table 1. At a significance level of 5% the restriction of one common factor was not rejected.

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

$$\frac{w' \left( \sum_{k=1}^m \tilde{\Lambda}_k \tilde{\Lambda}_k^H \right) w}{w' \left( \sum_{k=1}^m S_k \right) w} \quad (10)$$

where  $\tilde{\Lambda}_j$  is the maximum likelihood estimate of  $\tilde{\Lambda}_j$ , and  $w$  is a  $p \times 1$  vector of ones. Table 2 shows the decomposition of variation in unemployment across frequency bands for the common and sector-specific components.

Overall, 51% of the variation in unemployment is accounted for by common shocks. The magnitude is similar to Lilien's (1982 p. 778) 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% of movements in US output from 1948 to 1981 to sectoral factors and Forni and Reichlin (1998) who found 60% 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.

While our overall estimate of the contribution of sectoral shocks to unemployment movements is at least half, the split between the

**Table 1**  
Goodness of fit tests.

Frequencies	Likelihood ratio statistics CV at 0.05 is 91.67		
	Ordinates	Cycles per year	1 factor model $\chi^2(71)$
0–0.2 $\pi$	1:66	0–1.2	77.8
0.2 $\pi$ –0.4 $\pi$	67:132	1.2–2.4	49.9
0.4 $\pi$ –0.6 $\pi$	133:198	2.4–3.6	56.0
0.6 $\pi$ –0.8 $\pi$	199:264	3.6–4.8	26.9
0.8 $\pi$ – $\pi$	265:330	4.8–6	47.6

**Table 2**  
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

common and sectoral shocks varies greatly across frequencies. The low frequency variation of unemployment (including the business cycle frequencies of around 0.25 cycles per annum) is driven almost entirely by common shocks. At higher frequencies sectoral shocks dominate. This is consistent with the finding of Forni and Reichlin (1998, p. 471) that sectoral shocks to US output tend to be of high frequency.

The breakdown by sector of the sectoral contributions to unemployment movements is shown in Table 3. 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 sector 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 the volatility of core public sector employment.

#### 5. Results for Sub-periods

A question of interest is whether there are periods in which sectoral shocks were particularly important. We divided our data into three sub-periods, firstly the long post-war boom to 1969, secondly the rise in unemployment from 1970 through to 1983, and the subsequent period of strong growth from 1984 to the end of our sample in 2002. We tested the goodness of fit for the sub-period models, and the single common factor specification was not rejected for any sub-period.

The breakdown of movements in unemployment into common and sectoral components is given in Table 4. It is striking how dominant common shocks were during the large rise of unemployment in the 1970s, explaining 64% of the variation from 1970 to 1983, with a complete reversal for the 1984 to 2002 years of growth and falling unemployment, when common shocks only explained 30% of the variation.

**Table 3**  
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	

**Table 4**  
Variance decomposition of overall unemployment rate for sub-periods.

Cycles pa	Common %	Sectoral %	Total %	Common %	Sectoral %	Total %	Common %	Sectoral %	Total %
	Jan 48–Dec 69			Jan 70–Dec 83			Jan 84–Dec 02		
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

## 6. Discussion

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

Some possible candidates for the common factor are:

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

Some candidates for the sectoral factors are:

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

Do any of our factors look like technological change? There is little consensus about the frequency of technological change processes, but they are often thought to be of fairly low frequency. Crespo (2008) finds US Solow residuals concentrated at a period 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 by Forni and Reichlin (1998, p.465–66) who use an ingenious method (technology shocks must increase output) to identify technology as one of their two common factors driving sub-sectoral variation post-war US manufacturing output. This technological common factor is of low frequency, so if their identification is sound it provides evidence that technological change generates low frequency variation. Technological change is thus a plausible candidate for our low frequency common factor, and may also generate some of the high frequency variation behind the sectoral factors.

Neither theoretical considerations nor structural estimation literatures give enough evidence on the frequency of effective demand shocks to assess their plausibility as a candidate common shock.

Institutional and policy changes are low frequency events, and therefore are plausible candidates for the common shock, but not the sectoral shocks. If institutional and policy changes are important for unemployment 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.

## 6. 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 any 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 macro-economists 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 the criticism of Lilien's (1986) study, but our work, along with the studies of Norrbin and Schlagenhauf (1988), Forni and Lippi (1997), Forni and Reichlin (1998) suggest that sectoral shocks must be an important part of any explanation of the post-war US economic experience.

Since our test results support the hypothesis of a single common factor, the common factor is statistically identified up to a scalar transformation. In the context of a large static factor model, Bai and Ng (2006) develop a set of procedures for testing whether a set of observable variables spans the factor space. The development of similar procedures for the frequency domain maximum likelihood model would allow us to test whether observable variables, such as business cycle variables, macroeconomic policy variables, measures of technological change, etc., are scalar transformations of the common component of the sectoral contributions to unemployment. This may shed light on the issues discussed in Section 6. Of course, the development of such techniques is a non-trivial task which is well beyond the scope of the current paper. However, it will make an interesting topic for future research. Another area for future work is cross-country comparisons — comparing contributions of structural shocks in the US with Europe and Japan.

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