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# 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.



## 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 DYMIMIC 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)[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. 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)[2]. 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[3]. 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 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

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

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:

$$U_t = w'u_t \tag{2}$$

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.

[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.

[2] 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.

[3] 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.