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The Timing of Unemployment Response in Austrian Regional Labour Markets

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The Timing of Unemployment Response in Austrian Regional Labour Markets:
The Classical and an Alternative Mode of Exploratory Statistical Analysis

Manfred M. Fischer and Gerhard Petz

1. Introduction

In the past few years spatial labour market analysis has received increasing attention by economic geographers and regional economists. Three basic themes can be identified in current research on spatial labour markets (see Fischer and Nijkamp 1987). The first deals with issues such as the structure and change of labour supply, spatial dimensions of job search, commuting within and migration between spatial labour markets. The second theme concerns the analysis of the determinants of the demand side where the major focus is aimed at actual and likely future employment effects of spatial structural economic and broader technological changes. The third major area in current spatial labour market research refers to the analysis of spatial variations in unemployment.

Research activities in the third area have been stimulated in part by the problem of high and rising unemployment in most advanced economies over the past years. Much attention has been focussed on the question as to how the relative adjustment of unemployment in response to national forces arises over the space economy . This issue is important because it may provide valuable advices for the choice of appropriate instruments of regional labour market policy. In this context the timing of unemployment response plays a major role. There are several studies which have revealed the existence of response time differences in several countries. Brechling (1967), for example, identified in a British context a slight tendency for Scotland and North England of a lagged response (about three months) to national unemployment changes, while lags of one or two months were detected in Canadian and Australian studies.

In this paper an attempt is made to analyse the relationship between national and regional unemployment in general and the lead/lag structure of unemployment response in particular by means of exploratory statistical analysis, in an Austrian context. For this study, we had monthly observations of the unemployment rate in the nine Austrian provinces and the whole country as well. Thus, ten time series were at our disposal, covering the period from January 1961 until December 1986. Two major methodological approaches will be followed to identify any regularities in the relationship: first, the classical mode of analysis put forward by Brechling (1967) and subsequently widely used in a variety of settings and at different spatial scales, and second the transfer function-noise modelling approach which is strongly based upon Box and Jenkin's (1976) ARIMA methodology. These two different types of approaches will be described in some detail and applied to the time series at hand. The paper starts with pointing to some pecularities of the unemployment data used and with making some basic introductory descriptive comments about both national and regional patterns of unemployment.

2. Some Characteristics of the Data and the Unemployment Variation in Austria

The indicator of national and regional unemployment which is used in this study is the aggregate monthly registered labour reserve as a percentage of the labour force. The unemployed in Austria are defined as persons aged between 15 and 65 years who are resident in Austria, actively looking for work and have registered at the appropriate regional employment office. Persons out of work who do not register are not counted in the unemployment statistics. Persons seeking their first job, for example, young persons who register at one of the employment offices or seeking work after leaving school or finishing their studies are classified as unemployed if they are available at work.

It can be questioned to what extent the published unemployment data measure real unemployment. First, people looking for part-time jobs are neglected. Second, hidden unemployment present in the national sector of industry is not being measured. Moreover, there are people succeeding in doing unregistered work while being unemployed. Not very much is known how important this phenomenon is in Austria.

In this paper monthly observations on unemployment rates of Austrian provinces are used. Figure 1 displays a map of these provinces. It is worthwile to mention that the country's heartland is still located in the east even if the western provinces of Vorarlberg, Tyrol, Salzburg and Upper Austria have tended to gain economic importance in the past two decades. Moreover, it is noteworthy that Austria belongs to those few countries like Switzerland and Sweden which had greatest success in mastering unemployment during the international economic crises of the 1970s and early 1980s (see Fischer and Nijkamp 1987 for more details on this issue).

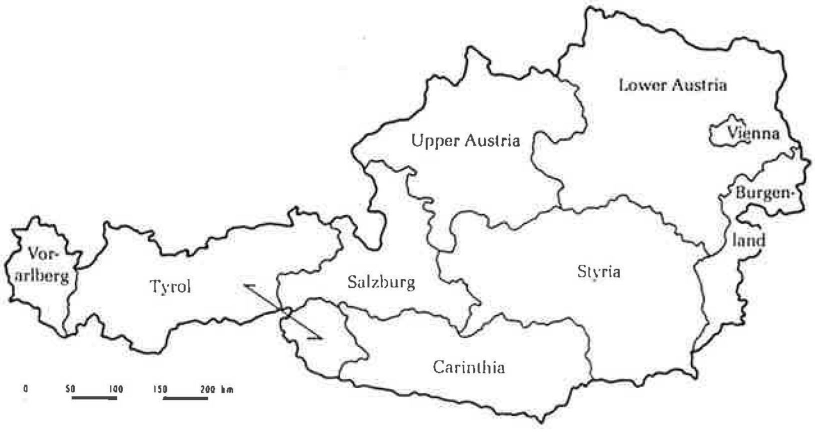

Figure 1. The Nine Länder of Austria for which Unemployment Data are Available.

The national and the 9 regional time series of unemployment rates are made up of monthly figures during the period of 1961-1986. Table 1 gives an indication of the overall situation during the period considered. Three indicators, the average unemployment level, the standard deviation and the coefficient of variation are utilized to characterize the ten time series. The latter two indicators express the stability of unemployment levels, the standard deviation in terms of absolute deviations and the coefficient of variation in terms of relative deviations from the average value over the whole period of consideration.

TABLE 1. Average Unemployment (1961-1986) and Stability Indicators.

Region	Average	Standard Deviation	Coefficient of Variation
Austria (A)	2.702	1.501	55.57
Vienna (VIE)	2.220	1.096	49.38
Lower Austria (LA)	3.636	1.270	34.94
Burgenland (B)	3.890	2.255	57.97
Styria (ST)	3.568	1.243	34.83
Carinthia (C)	5.871	2.641	44.99
Upper Austria (UA)	3.080	.840	27.27
Salzburg (S)	2.494	1.309	52.48
Tyrol (T)	3.196	1.930	60.40
Vorarlberg (V)	1.650	1.004	60.84

For initial descriptive purposes the evolution of the unemployment rate (based on yearly data) is presented in Figure 2 for the nine provinces in comparison to Austria as a whole. This figure clearly reveals that the period chosen for this study is essentially split up into two subperiods. The first one lasting until about 1981 is a 'plateau-like' period in which the national rate, for example, fluctuated around 2 per cent. The second one is a period of generally rising unemployment rates. By the end of the time series the national rate had reached the unemployment level of the 1950s again, around 5 per cent. The regional series exhibit a range of different characteristics. Their similarity to the national series in terms of response patterns is quite clear. But there is also evidence of more or less marked differences which exist between the different regional series in terms of their levels and their sensitivities to national economic events. In order to arrive at a more effective description of the regional series a quantitive approach is needed which enables to identify the regional response pattern to national events, to detect seasonal and other components of unemployment.

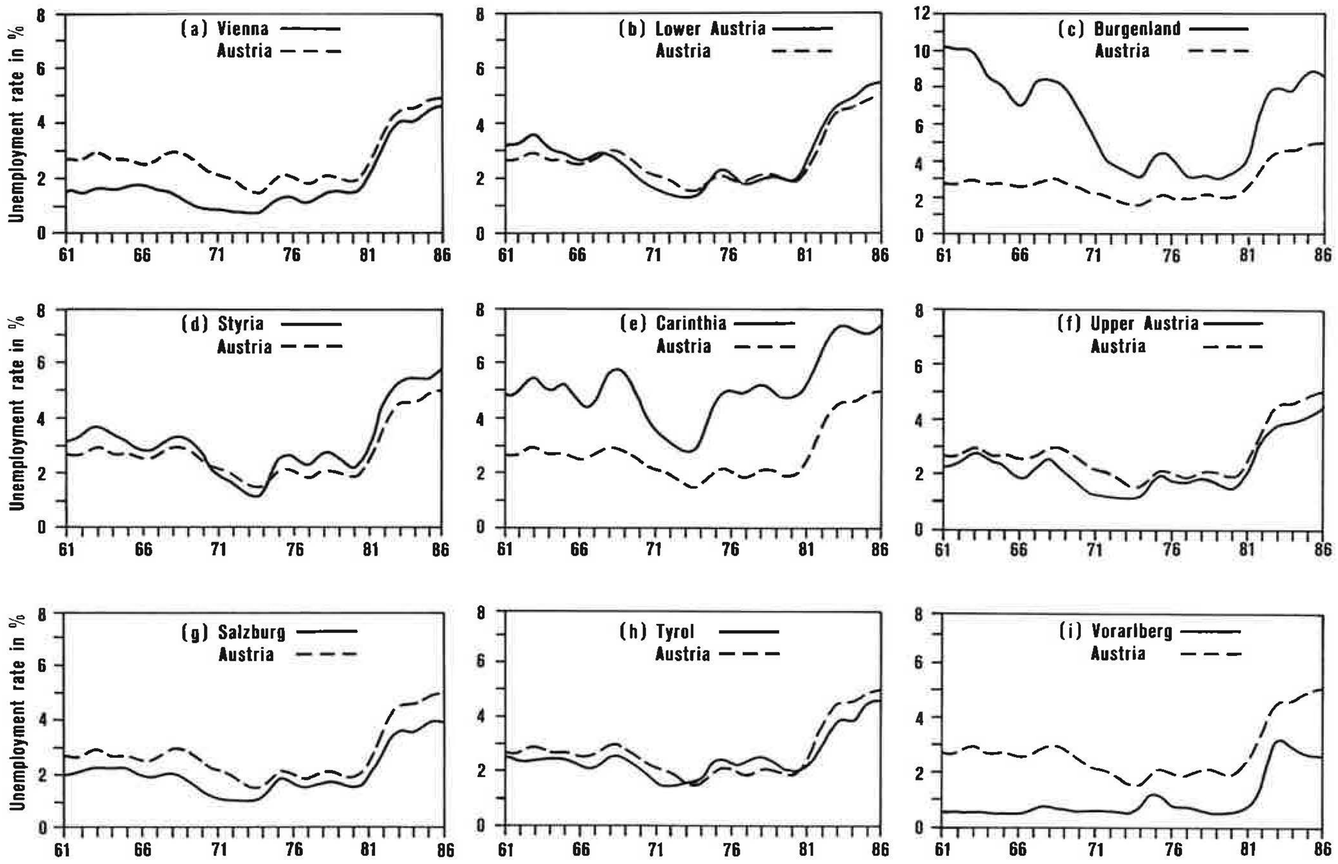

FIGURE 2: Unemployment in Austria (1961 — 1986) by Year and Province

3. The Classical Mode of Analysing the Relationship between National and Regional Unemployment

The approach which may be called the classical mode of analysing the relationship between national and regional unemployment is a basic descriptive model put forward by Brechling (1967) and subsequently used in a wide variety of settings and at different spatial scales (see, for example, King, Cassetti and Jeffrey 1972, Jeffrey 1974, King and Clark 1978, Frost and Spence 1981a, b). This approach measures the behaviour of individual regions relative to the national series and is based upon a regressional framework involving a set of time regressions in which the regional unemployment rate is related to structural, cyclical and seasonal components of unemployment. This relationship can be specified in a linear-additive form as follows:

$$U_{it} = L_{it} + C_{it} + S_{it} + \varepsilon_{it} \qquad (1)$$

and is thus often termed Brechling-type components model. In this model U_{it} denotes the unemployment rate in region i at time t; L_{it} the structural component, C_{it} the national cyclical component and S_{it} the seasonal component of region's i unemployment at t. ε_{it} is a region-specific error term representing measurement errors and additional influences on the unemployment level. This error term is usually interpreted as representing - at least partially - the unique regional component in the unemployment pattern such as plant closures, regional strikes, shifts in regional investment etc.

The non-cyclical or structural component of regional unemployment in (1) which expresses the long-term dislocations in labour market functioning brought about by structural shifts within the economic system can be and is usually estimated by use of a polynomial in time of second degree, i.e.

$$L_{it} = \alpha_{i0} + \alpha_{i1}\ t + \alpha_{i2}\ t^2 \qquad (2)$$

where α_{i0} denotes the level of structural unemployment at the initial time period; α_{i1} and α_{i2} are coefficients of the quadratic expression allowing for increases or decreases in the structural component at an increasing or decreasing rate over the total time period. The trend term reflects any tendency for the unemployment rate in region i to change systematically over time. In particular, variation in this term may be the effect of long run structural change or the result of a decline in the ability of the industries located in the region to generate demand for labour irrespective of any change in their composition or form. It is worthwile to mention that the choice of a quadratic trend is arbitrary even if nearly all applications of (1) limit the trend to only one turning point. But it would be possible to use higher powers of t.

The national cyclical component of region's i unemployment at time t, C_{it}, may be analytically specified as follows:

$$C_{it} = \alpha_{i3}\ U_{N\,t \pm b_i} \qquad (3)$$

where $U_{N\,t \pm b_i}$ denotes the national unemployment at time $t \pm b_i$, b_i indicates a region-specific lead or lag (in our case measured in months); α_{i3} a parameter measuring region's i sensitivity to national (cyclical) fluctuations in absolute terms (see Gordon 1985). If $\alpha_{i3}>1$, region i is more sensitive to fluctuations than the national series. If $\alpha_{i3}<1$, region i is less sensitive. Thus, this parameter may be interpreted as reflecting the strength, direction and significance of the impact which national unemployment fluctuation might have on regional unemployment in the short run. It is worthwile to note that the cyclical component C_{it} defined in this way is the orthodox Keynesian demand-deficiency conceptualization (Clark 1980).

Finally, the procedure commonly used to determine the constant additive seasonal component, S_{it}, consists of using seasonal dummies with value 0 or 1:

$$S_{it} = \alpha_{i4} Z_1 + \alpha_{i5} Z_2 + \dots + \alpha_{i14} Z_{11} \tag{4}$$

where $Z_1, Z_2, \dots, Z_{11}$ denote dummy variables which account for seasonal fluctuations (in our case each dummy is representing a certain month) and $\alpha_{i4}, \alpha_{i5}, \dots, \alpha_{i14}$ corresponding coefficients.

Thus, the particular form of the Brechling-type components model approach used in this study is as follows:

$$U_{it} = \alpha_{i0} + \alpha_{i1} t + \alpha_{i2} t^2 + \alpha_{i3} U_{N\, t\pm b_i} + \alpha_{i4} Z_1 + \alpha_{i5} Z_2 + \dots + \alpha_{i14} Z_{11} + \varepsilon_{it} \tag{5}$$

where the terms are as described above. Model (5) is based inter alia upon the following fundamental assumptions. First, the relationship between national and regional unemployment is linear in nature. Second, the disturbances have a zero mean and a constant variance. Third, the national unemployment variable is non-stochastic, i.e. $E(\varepsilon_{it}, U_{Nt})=0$ for all i. Fourth, the disturbances are not serially correlated, i.e. $E(\varepsilon_{it}, \varepsilon_{it-k})=0$ for $k\neq 0$ and for all i.

The model parameters in (5) were estimated for all i using the ordinary least squares procedure with a series of different leading and lagging national unemployment rates in order to determine the lag parameter b_i. Five different regressions were run for each regional series assuming $b_i=0,\pm 1$ and ± 2 for all i. The timing yielding the highest level of explained variation in U_{it}, in terms of the coefficient of determination R^2, was accepted as the 'best' representation of the process.

The associated parameter estimates as well as the corresponding R^2-values and the Durbin-Watson statistics, the d-values, are displayed in Table 2 for each region i. The main conclusions from the results of this table can be summarized as follows:

* First, the regions did not show a consistent tendency to react earlier or later than others to changes in national conditions. Of course, this does not imply that all the regions reacted at the same time to all national events. This finding simply indicates that the average tendency for a region to react early or late centred on zero for all regions over the time period considered. It is interesting to note that Frost and Spence (1981a) did find a similar result in a British context.

* Second, the national cyclical effect is strong and felt in all regions. Moreover, there are not only important interregional contrasts in the levels of unemployment, but also sharp differences among the regions in their sensitivity to national trends resulting in a clear spatial pattern of responsiveness. The eastern regions with the exception of Vienna stand out as being highly responsive to national changes (with $\hat{\alpha}_{i3}$-coefficients ranging from 1.13 for Lower Austria to a high of 3.80 for Burgenland), in sharp contrast to the western regions which were - with $\hat{\alpha}_{i3}$- coefficients ranging from 0.49 to 0.82 - consistently less sensitive to the national cyclical swings of levels of economic activity. The low senstivity of Vienna clearly confirms King and Clark's (1978) interpretation, in a Canadian setting, that large metropolitan areas tend to be insensitive as a result of economic diversity cushioning the impact of national cyclical fluctuations.

* Third, the structural or long term trend effect is much less important than the national cyclical effect and is , moreover, not in all cases significant. Carinthia stands out in showing a severe long term problem with respect to structural unemployment , reflected in the very high initial structural component. Furthermore, evidence suggests that structural unemployment in this region is slightly increasing at a slightly decreasing rate while in other regions such as, for example, Lower Austria. there seems to be a trend towards a slightly decreasing structural unemployment at a slightly increasing rate (of course considered over the whole time period).

* Fourth, the Durbin-Watson statistics indicate that all the regional series show more or less strong auto-correlation in the residuals. This suggests that there is some form of unique regional effect operating in the fluctuation of the unemployment levels over the time period considered.

Although Brechling models of type (5) have been used extensively in the past (see, for example, King and Clark 1978, Frost and Spence 1981a) and with some confidence in their ability to identify relationships between national and regional unemployment (Clark 1979), their adequacy and efficacy have been questioned more recently. In particular, criticism has focussed on two major shortcomings. First, the implicit assumption of a symmetry in the lead-lag relationship has been criticised (see Johnston 1983). This assumption implies that if a region leads the nation into a depression then it will also lead it out and if a region lags into the depression then it will also lag in the recovery stage. This assumption built in the classical mode of analysis is unwarranted both from a theoretical and an empirical point of view. The second objection refers to the fact that in nearly all applications the assumption of nonautoregression is violated. The presence of serial autocorrelation among the error terms has several serious implications. Even if the least squares estimates are unbiased in this case, they are likely to be inefficient. Moreover, the estimated variances seriously underestimate the true variances. The estimated variances, however, play an important role in constructing confidence intervals, testing hypotheses and computing t-ratios. Thus, even though the estimated parameters appear to be quite reliable (small variances) they are in fact extremely unreliable in the case of serially correlated errors. All these reasons suggest that generalizations concerning the patterns of national and regional unemployment relationships based upon the classical mode of analysis may be spurious.

TABLE 2. Estimated Coefficients of the Brechling-Type Components-Models (t-values in brackets).

Region	k_i	α_{i0}	α_{i1}	α_{i2}	α_{i3}	α_{i4}	α_{i5}	α_{i6}	α_{i7}	α_{i8}	α_{i9}	α_{i10}	α_{i11}	α_{i12}	α_{i13}	α_{i14}	R^2	d
VIE	0	0.24	−0.01$^{\times}$	6E − 05$^{\times}$	0.49$^{\times}$	−0.22$^{\times}$	-0.15	0.21$^{\times}$	0.51$^{\times}$	0.65$^{\times}$	0.71$^{\times}$	0.70$^{\times}$	0.69$^{\times}$	0.63$^{\times}$	0.45	0.25	0.940	0.284
		(1.73)	(-13.40)	(13.72)	(19.70)	(-2.55)	(-1.76)	(2.62)	(5.87)	(7.07)	(7.43)	(7.27)	(7.11)	(6.66)	(5.01)	(2.96)		
LA	0	0.45$^{\times}$	−0.01$^{\times}$	2E − 05$^{\times}$	1.13$^{\times}$	0.11	0.18$^{\times}$	0.15$^{\times}$	−0.36$^{\times}$	0.30	-0.12	-0.08	-0.11	−0.19$^{\times}$	−0.52$^{\times}$	−0.54$^{\times}$	0.978	0.423
		(3.29)	(-9.34)	(8.02)	(46.20)	(1.34)	(-2.18)	(1.94)	(-4.23)	(-3.40)	(-1.32)	(-0.84)	(-1.20)	(-2.14)	(-5.91)	(-6.55)		
B	0	1.41	0.003	−9E − 05$^{\times}$	3.80$^{\times}$	1.53$^{\times}$	-1.56	−2.56$^{\times}$	−4.98$^{\times}$	−4.32$^{\times}$	-3.46	−3.14$^{\times}$	−3.13$^{\times}$	−3.66$^{\times}$	−5.08$^{\times}$	−5.01$^{\times}$	0.928	0.463
		(1.48)	(0.48)	(-4.23)	(22.10)	(2.62)	(2.71)	(-4.56)	(-8.34)	(-6.86)	(-5.27)	(-4.73)	(-4.69)	(-5.59)	(-8.18)	(-8.55)		
ST	0	0.07	-0.002	5E-06	1.26$^{\times}$	0.25$^{\times}$	0.26$^{\times}$	0.05	−0.40$^{\times}$	−0.44$^{\times}$	−0.40$^{\times}$	−0.44$^{\times}$	−0.46$^{\times}$	−0.40$^{\times}$	−0.54$^{\times}$	−0.39$^{\times}$	0.975	0.343
		(0.43)	(-1.66)	(1.37)	(42.90)	(2.50)	(2.63)	(-0.49)	(-3.93)	(-4.12)	(-3.54)	(-3.86)	(-3.99)	(-3.60)	(-5.07)	(-3.94)		
C	0	2.01$^{\times}$	0.01$^{\times}$	−3E − 05$^{\times}$	1.54$^{\times}$	1.11$^{\times}$	0.88$^{\times}$	−0.05$^{\times}$	−1.87$^{\times}$	−2.98$^{\times}$	−3.56$^{\times}$	3.58$^{\times}$	3.54$^{\times}$	−3.15$^{\times}$	−1.90$^{\times}$	−1.12$^{\times}$	0.956	0.307
		(5.31)	(4.27)	(-4.15)	(22.63)	(4.88)	(3.86)	(-2.25)	(-7.97)	(-11.95)	(-13.70)	(-13.60)	(-13.40)	(-12.15)	(-7.71)	(-4.84)		
UA	0	0.02	−0.01$^{\times}$	1E − 05$^{\times}$	0.82$^{\times}$	0.02	0.02	0.17$^{\times}$	0.19$^{\times}$	0.20$^{\times}$	0.32$^{\times}$	0.34$^{\times}$	0.43$^{\times}$	0.37$^{\times}$	0.20$^{\times}$	0.11	0.966	0.389
		(0.22)	(-6.00)	(5.96)	(41.03)	(0.26)	(0.88)	(2.63)	(2.74)	(2.83)	(4.16)	(5.26)	(5.60)	(4.87)	(2.83)	(1.66)		
S	0	0.49$^{\times}$	−0.01$^{\times}$	2E − 05$^{\times}$	0.67$^{\times}$	−0.19$^{\times}$	−0.40$^{\times}$	−0.28$^{\times}$	0.23$^{\times}$	-0.13	−0.49$^{\times}$	−0.49$^{\times}$	−0.50$^{\times}$	−0.26$^{\times}$	0.58$^{\times}$	0.88$^{\times}$	0.962	0.721
		(4.14)	(-6.82)	(7.80)	(31.65)	(-2.7)	(-5.63)	(-4.06)	(3.20)	(-1.62)	(-6.10)	(-5.95)	(-6.12)	(-3.18)	(7.50)	(12.15)		
T	0	0.51$^{\times}$	4E-05	4E − 06$^{\times}$	0.75$^{\times}$	0.26	0.04	−0.35$^{\times}$	0.07	-0.08	−0.91$^{\times}$	−1.08$^{\times}$	−1.11$^{\times}$	−0.76$^{\times}$	0.45$^{\times}$	1.01$^{\times}$	0.933	0.789
		(2.56)	(0.03)	(0.96)	(20.92)	(2.17)	(0.35)	(-3.02)	(0.59)	(-0.62)	(-6.64)	(-7.80)	(-8.04)	(-5.58)	(3.46)	(8.30)		
V	0	−1.12$^{\times}$	0.002	5E − 06$^{\times}$	0.49$^{\times}$	−0.39$^{\times}$	−0.34$^{\times}$	0.04	0.59$^{\times}$	0.72$^{\times}$	0.63$^{\times}$	0.60$^{\times}$	0.57$^{\times}$	0.61$^{\times}$	0.77$^{\times}$	0.70$^{\times}$	0.843	0.300
		(-7.53)	(1.88)	(1.32)	(16.10)	(-3.71)	(-3.34)	(0.42)	(5.51)	(6.44)	(5.40)	(5.03)	(4.80)	(5.18)	(6.90)	(6.65)		

VIE : Vienna, LA : Lower Austria, B : Burgenland, ST : Styria, C : Carinthia, UA : Upper Austria, S : Salzburg, T : Tyrol, V : Vorarlberg

($^{\times}$) Coefficients are significant at the 0.05 level.

4. Transfer Function Modelling as an Alternative Mode of Analysis

In response to the above mentioned problems and deficiencies of the classical mode of analysis Clark (1979) and others suggested to use the transfer function modelling approach (more precisely the transfer function-noise model approach). This alternative mode of analysis shows some very attractive features. It can be used to describe a wide range of types of non-stationarity, seasonality and dynamic lag structures and to analyse the dynamic (or lagged) relationship by means of more general lag and error structures. The approach is not only more flexible in terms of identifying the relationships between national and regional unemployment in comparison with the classical mode. It also provides a great deal of flexibility in terms of characterizing the process which might be responsible for the autocorrelation among the error terms. A wide range of processes which can be generating the error terms may be taken into account.

The basic idea of the transfer function-noise model approach is to consider the dependent variable, U_{it}, and the independent variable, U_{Nt}, in the relationship between national and regional unemployment as realizations of underlying stochastic processes or in other words as realizations of jointly distributed random variables.

The general transfer function-noise model relating region's i unemployment to the national unemployment may be written as follows:

$$U_{it} = f_i(\kappa, U_{Nt \pm b_i}) + N_{it} \qquad (6)$$

where $f_i(\kappa, U_{Nt \pm b_i})$ is an adequate transfer function for region i relating the national unemployment rate U_{Nt} to the regional unemployment rate U_{it} and containing that part of U_{it} which can be explained exactly in terms of U_{Nt}; b_i is a region-specific lead/ lag paramter; κ a set of parameters characterizing the dynamic transfer of U_{Nt}; and N_{it} represents the noise component of the model representing the error structure of the national and the regional series. Referring to (6) two questions arise immediately, namely: which transfer function model candidate should be chosen and in which way the noise component should be specified. Answers to both these questions will be given in the sequel. The logic of the model building process based upon an iterative procedure is outlined in Figure 3 and essentially consists of four major stages.

The First Stage

The first stage serves to model the national and the regional unemployment series in such a way that the following two kinds of relationships are taken into account: correlations between successive observations within seasonal time periods and dependencies between different periods. This motivates to use model candidates out of the general class of multiplicative seasonal autoregressive integrated moving average (ARIMA) models which forms the most general and flexible key for specifying the univariate models, for example, for both regional and national unemployment. Such a multiplicative seasonal model for the national series can be formulated in the following shorthand form (see Box and Jenkins 1976, Fischer and Folmer 1982 for more details):

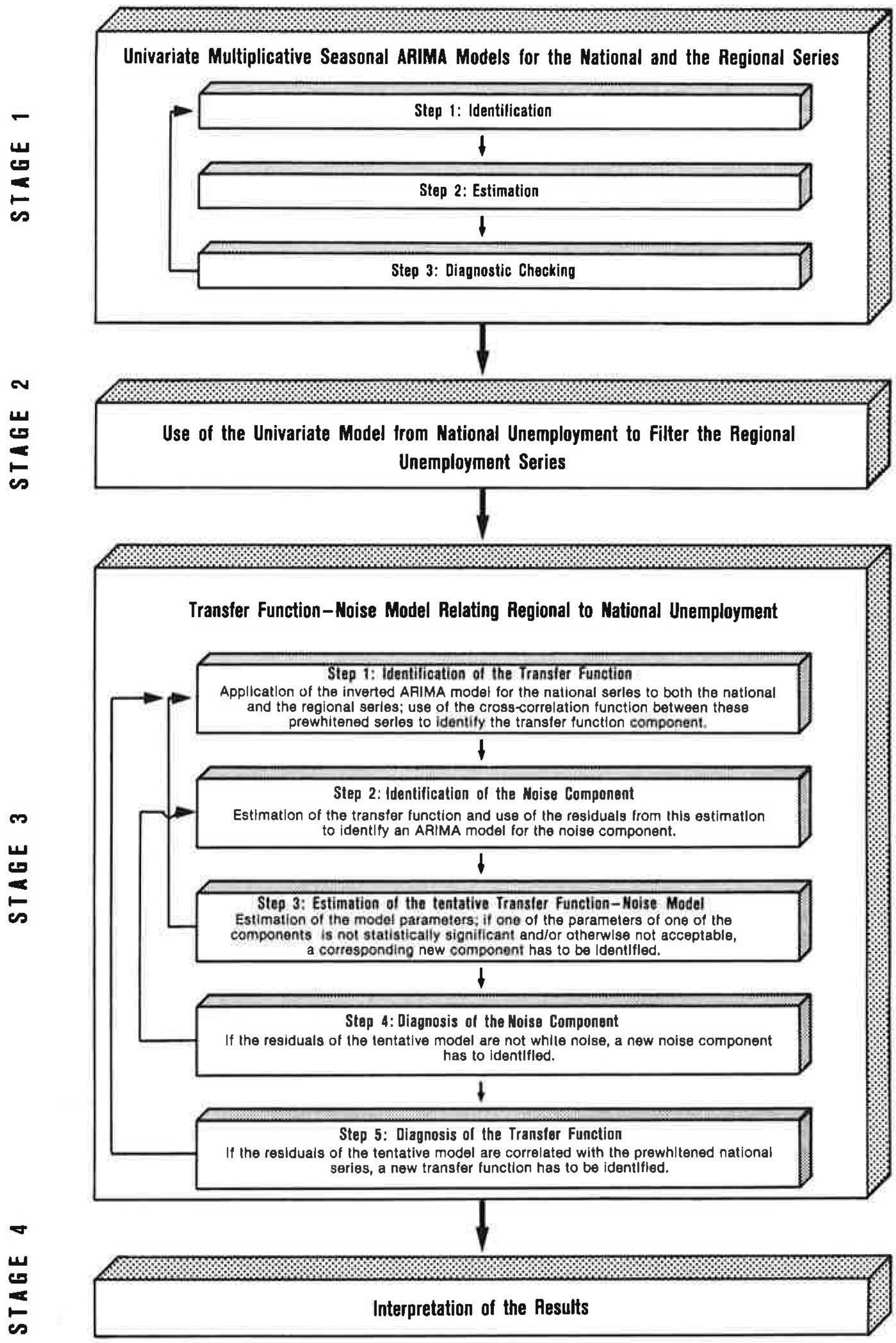

Figure 3. Stages in the Alternative Mode of Analysing the Relationship between National and Regional Unemployment (Source: Mc Cleary and Hay 1980)

$$\phi_{p_1}(B)\ \Phi_{p_2}(B^s)\ (1-B)^d\ (1-B^s)^D\ U_{Nrm} = \theta_{q_1}(B)\ \Theta_{q_2}(B^s)\ \beta_{Nrm} \tag{7}$$

where r and m are time indices corresponding to years r and months m; B denotes a backshift operator such that $B^k = U_{Nrm-k}$; $(1-B)^d$ and $(1-B^s)^D$ are the non-seasonal and the seasonal differencing operators, respectively.The underlying multiplicative process is said to be of order $(p_1, d, q_1)(p_2, D, q_2)_s$, where p_1 is the non-seasonal and p_2 the seasonal moving average order, q_1 the non-seasonal and q_2 the seasonal autoregressive order. The parameters d and D denote the degrees of seasonal and regular differencing. The non-seasonal autoregressive polynomial $\phi_{p_1}(B)$ and the non-seasonal moving average polynomial $\theta_{q_1}(B)$ are defined as

$$\phi_{p_1}(B) = 1 - \sum_{l=1,\ldots,p_1} \phi_l\ B^l \tag{8}$$

$$\theta_{q_1}(B) = 1 - \sum_{l=1,\ldots,q_1} \theta_l\ B^l \tag{9}$$

whereas the corresponding seasonal polynomials are determined by

$$\Phi_{p_2}(B^s) = 1 - \sum_{l=1,\ldots,p_2} \Phi_l\ B^{sl} \tag{10}$$

$$\Theta_{q_2}(B^s) = 1 - \sum_{l=1,\ldots,q_2} \Theta_l\ B^{sl} \tag{11}$$

It is apparent that the difference operator $(1-B)^d$ and its seasonal extension $(1-B^s)^D$ serve to remove non-stationarity characteristics of the homogeneous process, such as, for example, shifts in level. β_{Nrm} is a sequence of independently normally distributed random variables with mean zero and variance σ_β. In order to simplify notation it will be assumed in the sequel that the double indices rm in (7) are appropriately mapped on the set of positive integers and therefore only a single index, t, will be used.

The usual three step-iterative process of model identification, estimation of the identified model and diagnostic checking of the estimated model is utilized to arrive at a final model representation. For details on this issue compare, for example, Box and Jenkins (1976) and Fischer and Folmer (1982).

Model identification refers to the operation of selecting tentatively an adequate model and involves the use of rough data tools such as range-mean plots, autocorrelation and partial autocorrelation functions in order to get initial guesses of the degrees of differencing required to induce stationarity and the degrees of the polynomials appearing in the seasonal and non-seasonal autoregressive and moving average operators in (7). Whereas model identification is concerned with defining the structure of the model, parameter estimation is devoted to the determination of the magnitude and sign of the model parameters. In this paper a Gauss-Marquardt algorithm (implemented in the BMDP Program Version April 1985) is used to derive maximum likelihood estimates of the model parameters. Diagnostic checking, the final step of the model fitting process, involves checking on the adequacy of the identified and estimated model for the national unemployment data and moreover discovering if and in what respect the chosen model is inadequate or may be simplified. For a correctly specified model the residuals β_{Nt} should be close to white noise. This means that the residuals β_{Nt} should be random, serially uncorrelated and distributed as normal variates with mean zero and variance $(T\text{-}d\text{-}sD)^{-1}$ where T denotes the number of time points at which observations are available (see inter alia Bennett 1979, 244-245).

The modelling of the national unemployment series was relatively straightforward and thus needs not to be described in detail here. The national series contained significant trends, requiring non-seasonal differencing (d=1) to induce stationarity, and significant seasonal patterns (s=12), requiring further seasonal differencing (D=1) to induce stationarity in the seasonal behaviour. The final model arrived at was

$$(1 - B)\ (1 - B^{12})\ U_{Nt} = (1 -+ 0.15\ B + 0.25\ B^{11})\ (1 - 0.31\ B^{12})\ \beta_{Nt} \qquad (12)$$

(- 2.74) (- 4.68) (5.45)

The parameter estimates are statistically significant at the 95 per cent level and lie within the bounds of stationarity and invertibility. Moreover, the residuals are distributed as white noise. In particular the Q-statistic test implied no sigificant lack of fit. This univariate model for national unemployment is a prerequisite for the second stage of the model building process.

The univariate models for representing the regional unemployment series were derived in an analogous way. The structure of the models, their parameter estimates and Q-statistics are summarized in Table 3.These models are needed for two purposes; first so that the reduction in residual variance, as a result of introducing the input variable U_{Nt}, can be measured; and second to provide a first approximation to the structure of the noise component N_{it} to be used in the transfer function-noise model in stage 3 of the model building process.

TABLE 3. Univariate Models for the Regional Unemployment Series.

Region	Model Form	Parameter Estimates	(t-value)
1 Vienna	$\dfrac{(1-\theta_1 B^1-\theta_{11} B^{11})(1-\Theta_{12} B^{12})}{(1-B^1)(1-B^{12})}\,a_t$	$\theta_1 = -0.1721$	(-3.84)
		$\theta_{11} = -0.1441$	(-3.07)
		$\Theta_{12} = 0.5742$	(11.47)
2 Lower Austria	$\dfrac{(1-\theta_1 B^1-\theta_4 B^4-\theta_{11} B^{11})(1-\Theta_{12} B^{12})}{(1-B^1)(1-B^{12})}\,a_t$	$\hat{\theta}_1 = 0.1554$	(2.80)
		$\hat{\theta}_4 = 0.1167$	(2.16)
		$\hat{\theta}_{11} = -0.2326$	(-4.14)
		$\hat{\Theta}_{12} = 0.2625$	(4.72)
3 Burgenland	$\dfrac{(1-\theta_2 B^2-\theta_4 B^4-\theta_{11} B^{11})(1-\Theta_{12} B^{12})}{(1-\phi_1 B^1)(1-B^1)(1-B^{12})}\,a_t$	$\hat{\phi}_1 = -0.4468$	(-7.73)
		$\hat{\theta}_2 = 0.2790$	(4.58)
		$\hat{\theta}_4 = 0.1729$	(3.05)
		$\hat{\theta}_{11} = -0.2013$	(-3.73)
		$\hat{\Theta}_{12} = 0.1478$	(2.76)
4 Styria	$\dfrac{(1-\theta_{13} B^{13}-\theta_{14} B^{14})(1-\Theta_{24} B^{24})}{(1-B^1)(1-B^{12})}\,a_t$	$\hat{\theta}_{13} = -0.1989$	(-3.54)
		$\hat{\theta}_{14} = -0.1699$	(-3.01)
		$\hat{\Theta}_{24} = 0.2275$	(3.89)
5 Carinthia	$\dfrac{(1-\theta_2 B^2-\theta_3 B^3-\theta_{11} B^{11}-\theta_{13} B^{13})(1-\Theta_{12} B^{12})}{(1-B^1)(1-B^{12})}\,a_t$	$\hat{\theta}_2 = 0.2422$	(4.70)
		$\hat{\theta}_3 = 0.2049$	(4.22)
		$\hat{\theta}_{11} = -0.2475$	(-4.92)
		$\hat{\theta}_{13} = -0.1300$	(-2.36)
		$\hat{\Theta}_{12} = 0.3344$	(6.81)

TABLE 3 (ctd.).

Region	Model Form	Parameter Estimates (t-value)
6 Upper Austria	$\frac{(1-\theta_1 B^1-\theta_{11} B^{11}-\theta_{23} B^{23})(1-\Theta_{12} B^{12})}{(1-B^1)(1-B^{12})} a_t$	$\hat{\theta}_1 = -0.2432$ (-4.89) $\hat{\theta}_{11} = -0.3651$ (-6.58) $\hat{\theta}_{23} = 0.2134$ (3.73) $\hat{\Theta}_{12} = 0.3816$ (6.58)
7 Salzburg	$\frac{(1-\theta_{11} B^{11}-\theta_{13} B^{13})(1-\Theta_{12} B^{12})}{(1-B^1)(1-B^{12})} a_t$	$\hat{\theta}_{11} = -0.2496$ (-4.46) $\hat{\theta}_{13} = -0.1872$ (-3.34) $\hat{\Theta}_{12} = 0.2579$ (4.58)
8 Tyrol	$\frac{(1-\theta_1 B^1-\theta_{11} B^{11})(1-\Theta_{12} B^{12})}{(1-B^1)(1-B^{12})} a_t$	$\hat{\theta}_1 = 0.1303$ (2.30) $\hat{\theta}_{11} = -0.2415$ (-4.10) $\Theta_{12} = 0.2421$ (4.03)
9 Vorarlberg	$\frac{(1-\theta_1 B^1-\theta_{11} B^{11})(1-\Theta_{12} B^{12})}{(1-B^1)(1-B^{12})} a_t$	$\hat{\theta}_1 = 0.1338$ (2.67) $\hat{\theta}_{11} = -0.1469$ (-2.78) $\hat{\Theta}_{12} = 0.5352$ (10.14)

Note: In order to simplify notation the regional index i in the models has been dropped.

The Second Stage

In the second stage of the approach the inverted univariate model for the national series, which converts the correlated national unemployment series U_{Nt} into an (approximately) random series β_{Nt}, is applied to prewhiten each of the regional series, i.e.

$$(1 - B)(1 - B^{12})\, U_{it} = (1 + 0.15\ B + 0.25\ B^{11})(1 - 0.31\ B^{12})\, \gamma_{it} \tag{13}$$

converting them into other time series γ_{it} which will not be random in general.

The Third Stage

Stage 3 is devoted to the identification, estimation and diagnostic checking of a transfer function-noise model of type (6). As Figure 3 indicates, the first step in this task refers to the specification of the transfer function $f_i(\kappa, U_{Nt-b})$, for example, in the following way

$$f_i(\kappa, U_{Nt\pm b_i}) = \omega_i(B) \,/\, \delta_i(B)\ \ U_{Nt\pm b_i} \tag{14}$$

where the transfer function is represented by the ratio of two region-specific polynomials. The set κ of unknown parameters is disaggregated into two subsets $\boldsymbol{\omega} = (\omega_{i0}, \omega_{i1}, \ldots, \omega_{il_i})$ and $\boldsymbol{\delta} = (\delta_{i1}, \delta_{i2}, \ldots, \delta_{im_i})$. The polynomials $\omega_i(B)$ and $\delta_i(B)$ are defined as

$$\omega_i = \omega_{i0} - \omega_{i1} B - \ldots - \omega_{il_i} B^{l_i} \tag{15}$$

$$\delta_i = 1 - \delta_{i1} B - \ldots - \delta_{im_i} B^{m_i} \tag{16}$$

where l_i and m_i denote the degree of $\omega_i(B)$ and $\delta_i(B)$ respectively. In practice, however, it is hard for l_i and m_i to exceed 2. For stability reasons it is assumed that the roots of the characteristic equation $\delta_i(B)=0$ lie outside of the unit circle in the complex plane. This implies in particular that for the first-order transfer function model the parameter δ_{i1} satisfies that $-1< \delta_{i1}<1$, and for the second-order model the parameters δ_{i1} and δ_{i2} satisfy that $\delta_{i1} + \delta_{i2}<1$, $\delta_{i2} - \delta_{i1} < 1$ and $-1 < \delta_{i2} <1$ for all i.

The cross-correlation function between the prewhitened national unemployment series and each of the correspondingly transformed regional unemployment series - defined as the cross- correlation function between γ_{it} and β_{Nt} at different lags b_i - is estimated and used to identify a fransfer function model candidate. This is done in much the same way that the autocorrelation function is utilized to identify an ARIMA relationship within the national or the regional unemployment time series in stage 1.

TABLE 4. Estimated Coefficients of the Transfer Function Model:

Region	*Transfer Function Component*	*Noise Component*	*Parameter Estimates (t-value)*
1 Vienna	$\frac{\omega_0}{1 - \delta_1 B} U_{Nt}$	$\frac{(1 - \Theta_{12} B^{12})}{(1 - B^1)(1 - B^{12})} a_t$	$\hat{\omega}_0 =$ 0.1820 (9.14)
			$\hat{\delta}_1 =$ 0.2245 (3.11)
			$\hat{\Theta}_{12} =$ 0.5804 (11.53)
2 Lower Austria	$\omega_0 U_{Nt}$	$\frac{(1 - \theta_1 B^1 - \theta_2 B^2 - \theta_{11} B^{11})(1 - \Theta_{12} B^{12})}{(1 - B^1)(1 - B^{12})} a_t$	$\hat{\omega}_0 =$ 1.2230 (30.83)
			$\hat{\theta}_1 =$ 0.2326 (4.66)
			$\hat{\theta}_2 =$ 0.3408 (6.64)
			$\hat{\theta}_{11} =$ −0.1851 (−3.84)
			$\hat{\Theta}_{12} =$ 0.4815 (7.77)
3 Burgenland	$\frac{\omega_0}{1 - \delta_1 B} U_{Nt}$	$\frac{(1 - \theta_1 B^1 - \theta_{13} B^{13})(1 - \Theta_{12} B^{12})}{(1 - B^1)(1 - B^{12})} a_t$	$\hat{\omega}_0 =$ 4.8560 (21.97)
			$\hat{\delta}_1 =$ −0.1670 (−4.53)
			$\hat{\theta}_1 =$ 0.4176 (8.01)
			$\hat{\theta}_{13} =$ −0.3601 (−6.36)
			$\hat{\Theta}_{12} =$ 0.4255 (7.84)

Note: In order to simplify notation the regional index i in the models has been dropped.

TABLE 4 (ctd.).

Region	Transfer Function Component	Noise Component	Parameter Estimates (t-value)
4 Styria	$\omega_0 \, U_{Nt}$	$\frac{(1-\theta_1 B^1)(1-\Theta_{12} B^{12}-\Theta_{24} B^{24})}{(1-B^1)(1-B^{12})} a_t$	$\hat{\omega}_0 =$ 1.403 (34.55) $\hat{\theta}_1 =$ 0.0870 (1.97) $\hat{\Theta}_{12} =$ 0.4385 (7.42) $\hat{\Theta}_{24} =$ 0.3289 (5.30)
5 Carinthia	$\frac{\omega_0}{1-\delta_1 B} U_{Nt}$	$\frac{a_t}{(1-\Phi_{12} B^{12}-\Phi_{24} B^{24})(1-B^1)(1-B^{12})}$	$\hat{\omega}_0 =$ 2.246 (27.00) $\hat{\delta}_1 =$ 0.3570 (3.80) $\hat{\Phi}_{12} =$ −0.4476 (−7.64) $\hat{\Phi}_{24} =$ −0.3157 (−5.36)
6 Upper Austria	$\omega_0 \, U_{Nt}$	$\frac{a_t}{(1-\phi_1 B^1)(1-\Phi_{12} B^{12}-\Phi_{24} B^{24})(1-B^1)(1-B^{12})}$	$\hat{\omega}_0 =$ 0.7729 (22.28) $\hat{\phi}_1 =$ −0.1967 (−3.64) $\hat{\Phi}_{12} =$ −0.4237 (−7.99) $\hat{\Phi}_{24} =$ −0.2858 (−5.42)

TABLE 4 (ctd.).

Region	Transfer Function Component	Noise Component	Parameter Estimates (t-value)
7 Salzburg	$\frac{\omega_0}{1 - \delta_1 B} U_{Nt}$	$\frac{(1 - \theta_1 B^1 - \theta_2 B^2 - \theta_{13} B^{13})(1 - \Theta_{12} B^{12})}{(1 - B^1)(1 - B^{12})} a_t$	$\hat{\omega}_0 =$ 0.5676 (14.7)
			$\hat{\delta}_1 =$ 0.1756 (4.57)
			$\hat{\theta}_1 =$ 0.3778 (6.71)
			$\hat{\theta}_2 =$ 0.2512 (4.93)
			$\hat{\theta}_{13} =$ −0.1934 (−3.34)
			$\hat{\Theta}_{12} =$ 0.4632 (8.87)
8 Tyrol	$\omega_0 U_{Nt}$	$\frac{(1 - \theta_1 B^1 - \theta_3 B^3)(1 - \Theta_{12} B^{12})}{(1 - B^1)(1 - B^{12})} a_t$	$\hat{\omega}_0 =$ 0.8456 (14.26)
			$\hat{\theta}_1 =$ 0.4005 (7.9)
			$\hat{\theta}_3 =$ 0.1542 (3.12)
			$\hat{\Theta}_{12} =$ 0.2652 (5.17)
9 Vorarlberg	$\omega_0 U_{Nt}$	$\frac{(1 - \theta_1 B^1 - \theta_8 B^8)(1 - \Theta_{12} B^{12})}{(1 - B^1)(1 - B^{12})} a_t$	$\hat{\omega}_0 =$ 0.2553 (7.45)
			$\hat{\theta}_1 =$ 0.2205 (4.67)
			$\hat{\theta}_8 =$ 0.172 (3.87)
			$\hat{\Theta}_{12} =$ 0.5323 (10.85)

In the second step the parameters of the identified transfer function component are estimated. The residuals from this estimation are utilized to identify an ARIMA model for the noise component N_{it} of the following type:

$$\phi_{p_1}(B) \quad \Phi_{p_2}(B^s) \quad (1-B)^d \quad (1-B^s)^D \quad N_{it} = \theta_{q_1}(B) \quad \Theta_{q_2}(B^s) \quad a_{it} \tag{17}$$

As a first guess of the structure of this component the univariate models for U_{it} derived in stage 1 may be used. Then in the next step the models of the fully identified transfer function-noise model are estimated. All the estimated parameters have to fulfill the usual requirements. If the parameter estimates of one of the two components are unacceptable, then a new component has to be identified. The adequacy of the noise model has to be checked in the fourth step. This is done in the same manner that an univariate ARIMA is diagnosed. If the residuals of the tentative model are not white noise, a new noise component model has to be identified. Finally, the transfer function component has to be diagnosed. If the residuals of the tentative model are correlated with the prewhitened national unemployment series, a new transfer function has to be specified. A statistically adequate transfer function component has to be independent of the noise component. If this is not the case there will be spikes at the low-order lags of the cross-correlation function (see Cleary and Hay 1980).

Following this procedure each regional transfer function-noise model was independently modelled and checked until after some iterations of estimating and diagnostic checking the final model forms could be estimated with confidence. These final models together with their parameter estimates and the corrresponding Q-statistics are summarized in Table 4.

Stage 4

The final stage refers to the interpretation and discussion of the results obtained in stage 3. The following comments can be made, first with respect to the noise and then with respect to the transfer function components.

It is worth reminding that - quite in contrast to the classical mode of analysis - the error structure is a vital element in the alternative modelling process. Thus, it is not surprising that Table 3 shows more or less large differences in the different regional noise components, indicating the importance of regional factors affecting regional unemployment behaviour. A twelve month seasonal factor incorporated in all the regional models exhibits strong seasonal behaviour. Only in the case of Tyrol the seasonal effect is weaker. In particular rather strong periodic components evidenced by twelve and twenty-four seasonal factors can be found in Styria, Carinthia and Upper Austria. There are also differences in the parsimony of the error structure models. In the Vienna case only one parameter is needed to describe adequately the structure of autocorrelation in the residuals, leading to a $(0,1,0)\ (0,1,1)_{12}$ - model which contains no non-seasonal components. It is interesting to note that the Viennese noise component simplified greatly during the model building process starting with the univariate model as a first approximation (compare Table 3). The other error structures are more complex, especially in the case of Lower Austria with 3-parameter non-seasonal and 1-parameter seasonal moving average operators and in the case of Salzburg with 2-parameter non-seasonal and 2-parameter seasonal moving average operators.

With respect to the issue of the relationship between national and regional unemployment and the results displayed in Table 4, several generalizations can be made. First, all the transfer function models show a zero time lag (i.e. $b_i=0$ for all i) more or less unambiguously indicated by spikes of the corresponding cross-correlation function at zero. The high degree of spatial aggregation necessitated by the problem of data availability certainly obscures a more differentiated lead/lag structure . Second, the models exhibit a rather simple relationship between national and regional unemployment, simpler in any case than one may have suggested.

Third, two types of relationships have been identified and estimated: zero-order and first-order transfer functions. For Lower Austria, Styria and Upper Austria the relationship between national and regional unemployment rates is represented by a zero-order model, the simplest possible transfer function component

$$f_i(\kappa, U_{Nt\pm b_i}) = \omega_{i0} \; U_{Nt\pm 0} \qquad \text{for } i = 2, 4, 6 \text{ and } 8 \qquad (18)$$

This transfer function model causes the regions to react simultaneously with the national series and not to lead or lag in response. to national impulses. In other words, the regions exhibit consistent behaviour with respect to the national series. There is *no dynamic* transfer of national changes in the unemploymen rate.

The other type of relationship between national and regional unemployment represented by a first-order transfer function component

$$f_i(\kappa, U_{Nt\pm b_i}) = \{\omega_{i0}/(1 - \delta_{i1} \; B)\} \; U_{Nt\pm 0} \qquad \text{for } i = 1, 3, 5, 7 \text{ and } 9 \qquad (19)$$

is realized in all the other regions, namely in Vienna, Burgenland, Carinthia and Salzburg. This model describes a dynamic 'causal' relationship between the two time series and indicates that a change in national unemployment is followed by an asymptotic change in the region's unemployment.

Given this general description of the structure of the transfer function-noise models, let us consider the parameter estimates of the transfer function component now. It is worth noting that all the parameter estimates are statistically significant. Following Clark (1979) it is assumed that a $\hat{\omega}_{i0}$ - value greater than unity implies that region i tends to be more sensitive to cyclical fluctuations than the national series, while a value less than unity implies that the region is, on average, less sensitive to short-run fluctuations. Table 4 reveals a clear pattern of interregional variation in the cyclical sensitivity of unemployment. The eastern regions (except Vienna with a value of $\hat{\omega}_{10}=0.18$) characterized by values ranging from a low of 1.22 (Lower Austria) to a high of 4.86 (Burgenland) are much more sensitive than the Wwestern regions with values ranging from 0.26 (Vorarlberg) to 0.85 (Tyrol). This result essentially coincides with that one obtained by the classical mode of analysis.

The asymptotic impact indicated by a first-order transfer function model is generally realized at a rate determined by δ_{i1} which may be interpreted as a rate parameter. When $\hat{\delta}_{i1}$ is larger, near unity for example, than the asymptotic impact of national events is being realized slowly. When $\hat{\delta}_{i1}$ is small the asymptotic impact tends to be realized rather quickly. This seems to be more or less the case in all the regions represented by a first-order transfer function relationship, less in Carinthia ($\hat{\delta}_{51}$=0.36) than in Vienna ($\hat{\delta}_{11}$=0.36) and especially in Salzburg ($\hat{\delta}_{71}$=0.18) and Burgenland ($\hat{\delta}_{31}$=0.17).

5. Concluding Remarks

One major empirical conclusion from this exploratory analysis is that at the provincial scale there is no evidence in the time series between 1961 and 1986 to suggest that any province shows consistent tendencies for the timing of its unemployment responses to be different from that of the other provinces. In other words, the existence of lags or leads at this level of spatial aggregation can be denied. This conclusion, however, does not negate that , for example, at the level of local labour markets timing differences in the reaction to economic national events might exist in certain areas.

Concerning the sensitivity of the regions to national events, both the classical mode of analysis and the transfer function-noise modelling approach led to the same global conclusions, namely to a clear spatial pattern of responsiveness. The eastern regions (except Vienna) stand out as being highly responsive to national changes while the western regions are consistently much less sensitive. Vienna tends to be insensitive . A possible explanation for Vienna's insensitivity might be its economic diversity cushioning national cyclical fluctuations. But the causes of this insensitvity remain, in this exploratory study, in the realms of speculations and would require a more detailed explanatory analysis.

From a methodological point of view, the analysis of the relationship between national and regional unemployment clearly illustrated the superiority of the transfer function-noise modelling approach. This superiority is essentially based upon its greater flexibility , first to explore interregional differences in the dynamic transfer of national events through identifying transfer functions, and second to integrate directly the autocorrelation properties of the time series through identifying quite complex multiplicative autocorrelated error structures.

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