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*AN ERROR CORRECTION-  
BAYESIAN VECTOR AUTOREGRESSION APPROACH*

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## *AN ERROR CORRECTION-BAYESIAN VECTOR AUTOREGRESSION APPROACH*

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### **Abstract:**

In forecasting sectoral employment, information from input output tables has been used to improve forecast performance by explicitly taking into account intersectoral linkages. In a Bayesian Vector Autoregression framework, I-O information has been used for specifying prior variances and prior means, respectively.

This paper pursues a somewhat different approach by incorporating an error correction mechanism in a (Baysian) VAR. The error correction term is derived not from a Vector Error Correction model but from an I-O model which is specified in terms of employment. The I-O model itself is set up on the basis of the 1995 input output table of Austria along with sectorally disaggregated employment data provided by the Social Security agency. Results from this I-O model are incorporated as an error correction mechanism into otherwise standard VAR and BVAR models.

The first part of the paper presents the derivation of the I-O model. The second part presents estimation results for the "EC-BVAR" model and gives an assessment of its relative merits by means of a comparison with the performance of single-equation ARIMA and "standard" VAR and BVAR models.

**Keywords:** Employment, Forecasts, Input Output, Bayesian VAR

**JEL Classification:** C11, C32, D5, J21

# 1 INTRODUCTION

Employment forecasts make for somewhat tricky exercises: if one uses structural models of the underlying economy, the problem is that it is the economic development which has to be got right first; deducing the employment reaction therefrom comes only afterwards (but no less difficult). But of course, in order to get the broad picture, the structural approach is indispensable.

Additionally, there is only so much which economic models can do. Typically, if they are sectorally disaggregated at all, they are so in a rather crude fashion. Another point is that their frequency is rarely, if ever, higher than quarterly; more often they are set up on an annual basis.

The last point concerns data availability: for structural models using national accounting data, the most recent observations might be a few quarters, sometimes even years, back.

Compared with national accounting data, wage employment data are ridiculously up-to-date, frequent, and accurate. In the case of Austria, the Social Security Agency provides, with a delay of less than a month, wage employment data on a monthly basis, disaggregated into 55 industries. For these reasons, time series methods are an attractive choice when one is confronted with the task of providing employment forecasts.

One of the weak points of time series methods is their “data-credulity”; the effects that external shocks might exert are not easily modelled; the same is true for potentially valuable information which could be derived from economic interdependencies. To address this last issue, an interesting approach has been developed in the 1990’s, involving Bayesian estimation of Vector Autoregression models, in which the prior beliefs entering the model are derived from Input Output tables.

This is where the present paper attempts to build upon. The paper is organized in the following way: First, in chapter 2, a brief description of the data set is provided. The second part gives an overview of forecasting models which were applied to sectoral employment together with the derivation of inter-sectoral employment relationships from classical Input Output Tables; two approaches to include those IO relationships in forecasting models are presented. The forecasts generated using these along with other, more conventional models are compared in Chapter 3.2. Finally, conclusions are drawn and possible directions of future research outlined.

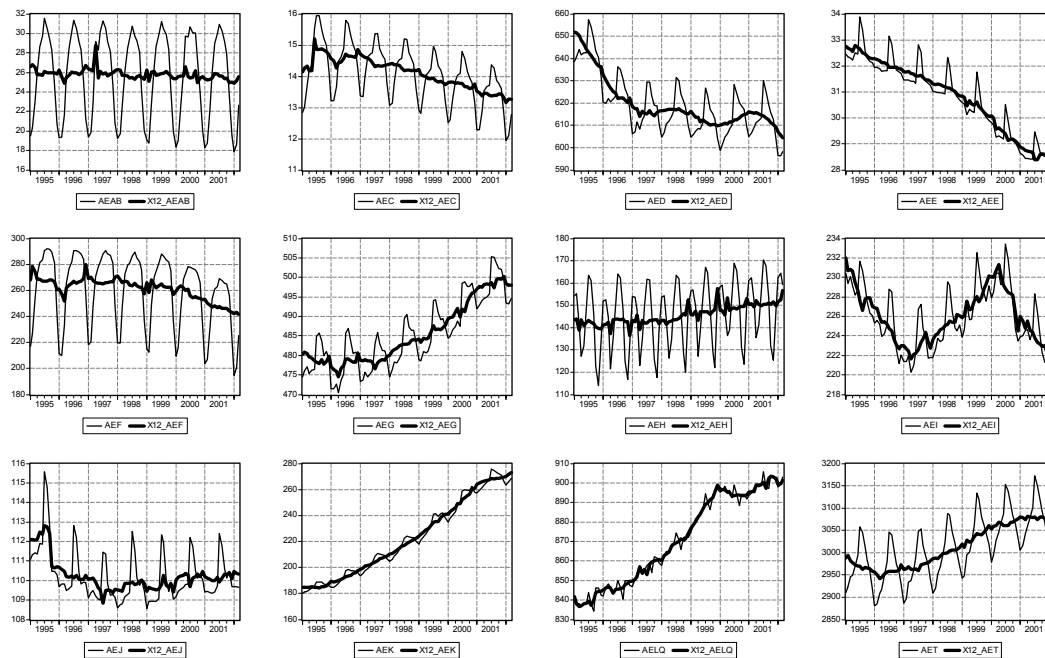
## 2 DATA DESCRIPTION

Wage employment is predicted for eleven groups of 1-digit NACE sectors of the Austrian economy. These comprise the following sectors:

A/B	Agriculture, Hunting and Forestry, Fishing
C	Mining and Quarrying
D	Manufacturing
E	Electricity, Gas and Water Supply
F	Construction
G	Wholesale and Retail Trade, Repair of Motor Vehicles
H	Hotels and Restaurants
I	Transport, Storage and Communications
J	Financial Intermediation
K	Real Estate, Renting and Business Related Services
L-Q	Public Administration, Education, Health, Other Personal Service Services

Monthly data were provided by *Hauptverband der Sozialversicherungsträger (HVSF)*, the Austrian Social Security Agency. In 2001, average total wage employment in Austria amounted to 3,078,270 employees. Data were available on a monthly basis from January 1995 through March 2002<sup>1</sup>, which sums up to a total of 87 monthly data points.

Figure 1: Austrian wage employment by 1-digit NACE industries, 1995:01-2002:03, in Thousands.



Source: HVSF

<sup>1</sup> prior to Austria's accession to the European Union in 1995, with the industry classification system BS68 a different system of industry classification was in use, which on the aggregate level is not compatible with the current NACE system.

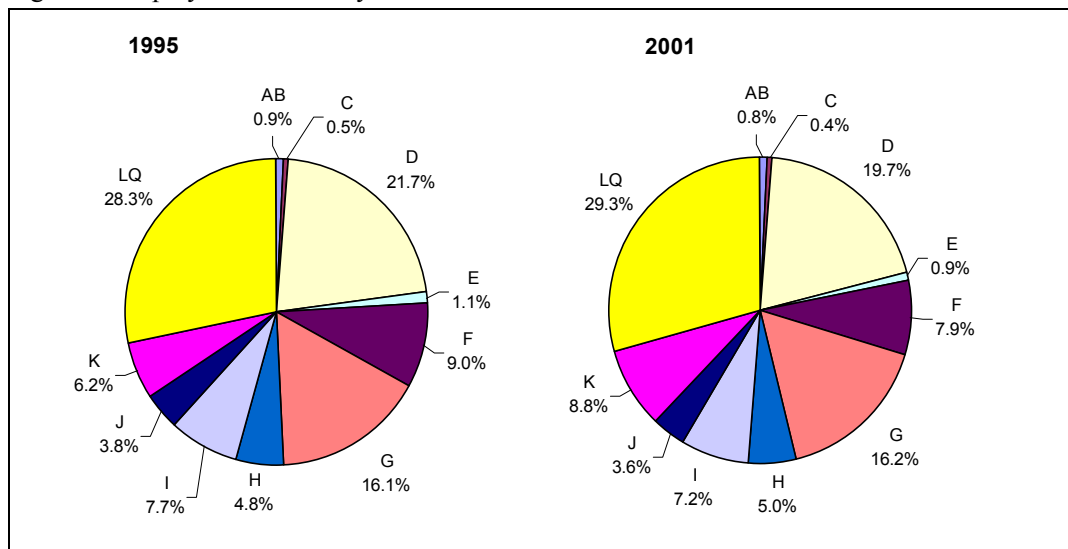
Figure 1 depicts the historical series, together with their de-seasonalized counterparts, for Austrian wage employment ranging from January 1995 to March 2002, the last observation available. Most series exhibit clear seasonality, least so - and unsurprisingly - employment in sectors L-Q (Public Administration, Education, Health, Other Personal Service Activities). For the analyses, all series were de-seasonalized using the Census Bureau's X12-procedure as implemented in EViews 4.0.

Apart from the first year, 1995, total wage employment exhibits a stable upward trend, averaging about +0.9% per year, until, from the beginning of 2001, growth started levelling off. Since the last quarter of 2001, growth rates have turned slightly negative.

Figure 2 below shows average employment shares of the 11 sectors for the years of 1995 and 2001. Four sectors were able to expand their share in total employment, strongest of them sector K, *Business-related services*, which was able to gain more than 40% by moving from 6.2% of total employment to 8.8%. Less spectacularly, sectors L-Q (*Public Administration, Education, Health, Other Personal Service Activities*), H (*Restaurants and Hotels*), and, albeit to a very slight degree only, sector G (*Wholesale and Retail Trade*) contributed to the secular move towards the "service-oriented economy".

The losers, on the other hand, can be found in the primary and secondary sectors of the economy: sector AB (*agriculture, forestry, fishery*) lost about 7% of its employment share<sup>2</sup>. Sectors C, E, and F (*Mining and Quarrying; Electricity, Gas and Water Supply; and Construction*) each lost around 15% of their shares, sectors D and I (*Manufacturing and Transport and Communications*) lost about 9% and 6%, respectively. The only exception to the "services gain" pattern is made up of sector J (*Financial Intermediation*), which lost about 5% in relative size. The reason for this, however, can be found in the fact that, in the past, Austria was famously "overbanked".

Figure 2: Employment Shares by Sector



Source: HVSV

<sup>2</sup> this number under-estimates the real decline in agricultural employment by a factor of almost 2, because in Austria, this sector is heavily dominated by small-scale farms run mostly by their owners and their families.

### 3 Estimation, Forecasting and Forecast Evaluation Methods

The main purpose of this exercise is to contrast the forecasting performance of different estimation methods. These methods include:

- single equation ARIMA-models
- Vector Autoregression Methods:
  - Unrestricted VAR
  - Bayesian VARs utilizing the Minnesota Prior
- Error Correction Models within an autoregressive framework.

As the objective is to forecast Austrian sectoral employment, the different methods were compared with respect to their forecasting performance. This was done on the basis of ex post forecasts. The models were first estimated for different sub-samples, all of which start in 1995:01 and end between 2000:01 and 2002:02, respectively, and forecasts were generated for the remaining sample of the historic time series up to 2002:03.

For each of the 25 iterations of the rolling regression exercise, the forecast horizon was set at 24 steps. As a result, a total of 25 1-step ahead forecasts, 24 2-step ahead, 23 3-step,... all the way to 2 24-step ahead forecasts were generated. These were then compared to their respective actual employment levels. The mean absolute percentage error (MAPE) was used to evaluate the forecasts. Total employment was not modeled separately, but was calculated as the sum of the forecasts for the different sectors.

#### 3.1 METHODOLOGICAL CONSIDERATIONS

##### 3.1.1 Unrestricted VARs

Vector Autoregressions belong to "nonstructural models", in that relationships between variables are not based on economic theory. In VARs, the design matrix consists of lagged values of all variables; under the assumption that the error terms are uncorrelated over the variables, such VARs can be estimated using OLS. As introduced by Sims (1980), VARs are specified via the largest number of lags uniformly to be applied to all variables. All equations in a VAR, therefore, share a common set of independent variables. In an extension to Sims' approach, additional exogenous variables can be introduced. So-called NearVARs, then, use different lag structures for the equations, thereby parting with the common design matrix. As long as only lagged variables are used in the right hand side (and the error terms are uncorrelated between equations), though, OLS remains appropriate.

##### 3.1.2 Bayesian VARs

This approach intends to incorporate "prior information" as to the coefficients of the VAR; however, it doesn't incorporate this information as "deterministic restrictions", but rather as "stochastic suggestions", centering the estimated coefficients somehow on the prior beliefs but not forcing the estimation process towards any presupposed outcome; this is accomplished by defining prior means and variances for all coefficients. The larger the variance, then, the further the estimation outcome is

allowed to deviate from the prior means. Estimation of such models can be carried out using Theil's Mixed Estimation technique.

This approach was introduced by Litterman (1980). In his specification, the prior belief is that each equation follows essentially a random walk. Accordingly, the prior mean of the first own-lag coefficient for each variable is set to 1, the other coefficients (higher own-lags as well as cross-lags) are set to 0 (implying the random walk specification  $x_{i,t} = x_{i,t-1} + \text{error}$ ).<sup>3</sup>

To cope with the infinite number of possible specifications of the variances around the prior means, Litterman suggested to use a set of "hyperparameters", which govern the pattern of the variances  $\lambda_{ij}$  according to

$$\lambda_{ijk} = (\theta f_{ij} g(k) (S_i / S_j))^2$$

where

- $\theta$  a general term for the sizes of the variances, the overall "tightness" parameter,
  - $f_{ij}$  the relative tightness around the prior mean of the coefficient relating variable  $i$  to all lags of variable  $j$ , and
  - $g(k)$  a "lag decay" function to tighten the distribution around the prior mean for greater lag lengths (similar to the specification of Almon or Koyck lags in Distributed Lag Models, thus dramatically reducing the number of free parameters).
- $S_i$  and  $S_j$ , then, are the standard errors of respective univariate regressions for variables  $i$  and  $j$ , a scaling term to account for different magnitudes of variables  $i$  and  $j$ .

A variant of this method came to be known as the "Minnesota Prior" (Todd (1984), Crone and McLaughlin (1999)). Here, the relative tightness  $f_{ij}$  of the variances around their prior means is typically set at 1.0 for the first own lags and 0.5 for all the other coefficients.

### **3.1.3 Derivation of Employment Input Output Relationship**

An extension of the Bayesian approach is outlined in LeSage and Magura (1991) and Partridge and Rickman (1998), who used information from IO tables, i.e. the technical coefficients, to further refine the relative variances of the coefficients around their prior means. Whereas the former used the technical coefficients as information about the variances (if two sectors are highly interdependent, meaning that the one sector uses a significant amount of inputs from the other, the respective cross lag coefficients are allowed to depart further from the prior mean of 0), the latter took this idea one step further by using the technical coefficients to determine the values of the prior means themselves. Moreover, their exposition also incorporates "indirect" effects, by taking into account demand effects, as income generated by one sector feeds back into final demand for the outputs of other sectors.

Information from the Input-Output relationships enters the analysis in the following way (the exposition draws heavily on Partridge and Rickman (1998)):

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<sup>3</sup> Remark: when modeling I(1)-variables in differences, this random walk prior implies first own-lag coefficients of 0!

The row equation of an IO-model is

$$Q_i = \sum_{j=1}^n (\alpha_{ij} Q_j) + \alpha_{iC} C + \alpha_{iG} G + \alpha_{iX} X + \alpha_{iI} I.$$

The sum term captures the other sectors' intermediate demand for output from sector  $i$ . The last four terms represent components of final demand (here, private consumption  $C$ , government expenditure  $G$ , exports  $X$  and investment  $I$ ). The  $\alpha_{ij}$ 's are the technical coefficients relating output of sector  $i$  to output of sector  $j$ . The coefficients  $\alpha_{iC}$  to  $\alpha_{iI}$  are the shares of the respective components of final demand composed of output of sector  $i$ .

As we are interested in employment relationships, however, this row equation is written in terms of employment in sector  $i$ . To do this, we assume constant ratios  $\beta_k$  of employment to output in sector  $k$ , so  $Q_k = E_k/\beta_k$ . Therefore,

$$E_i = \beta_i \left[ \sum_{j=1}^n \left( \frac{\alpha_{ij}}{\beta_j} E_j \right) + \alpha_{iC} C + \alpha_{iG} G + \alpha_{iX} X + \alpha_{iI} I \right].$$

To express final demand in terms of employment, we assume linear relationships between final demand and wage income. With  $W_h$  being the average wage rate in sector  $h$ , and the assumption that the components of final demands other than exports can be determined endogenously<sup>4</sup>,

$$E_i = \beta_i \left[ \sum_{j=1}^n \left( \frac{\alpha_{ij}}{\beta_j} E_j \right) + \alpha_{iC} \gamma_C \sum_{j=1}^n E_j W_j + \alpha_{iG} \gamma_G \sum_{j=1}^n E_j W_j + \alpha_{iI} \gamma_I \sum_{j=1}^n E_j W_j + \alpha_{iX} X \right]$$

with  $W_j$  the wage rate in industry  $j$ , and  $\gamma_C$  to  $\gamma_I$  the ratios of final demand to wage income. Rearranging the sum, we can write

$$E_i = \beta_i \left[ \sum_{j=1}^n \left( \frac{\alpha_{ij}}{\beta_j} + \alpha_{iC} \gamma_C W_j + \alpha_{iG} \gamma_G W_j + \alpha_{iI} \gamma_I W_j \right) E_j + \alpha_{iX} X \right]$$

or, more compactly,

$$E_i = \sum_{j=1}^n \psi_{ij} E_j + \alpha_{iX} X \quad \text{with} \quad \psi_{ij} = \beta_i \left( \frac{\alpha_{ij}}{\beta_j} + \alpha_{iC} \gamma_C + \alpha_{iG} \gamma_G + \alpha_{iI} \gamma_I \right)$$

The  $\psi_{ij}$  are the average ratios of the employment in sector  $i$  to the employment in sector  $j$ , taking into account all components of final demand besides exports. We have now arrived at reduced-form

<sup>4</sup> for private consumption, this assumption seems straightforward, as it is to a large degree determined by wage income. Government consumption, being constrained by the governments ability to raise taxes – which themselves heavily depend on wage and income taxes as well as consumption tax – also seems reasonably to be linked to wage income. For investment, the assumption constitutes more of a stretch, the rationale being that investment depends on output, which in turn depends on (private and government) demand as well as on exports.

Now, exports clearly do not fit into this line of argument. Therefore, exports are excluded from the Input Output model in that their levels are supposed to be constant. In reality, this is clearly not the case. Nevertheless, in the following “dynamization” of the I-O relationships, changing levels of exports should be taken care of.



expressions for the employment levels of our 11 sectors, linking the level of employment in each sector to the levels of all other sectors.

Exports are still treated as exogenous, and will remain so throughout the rest of this paper. Indirectly, however, effects brought about by changing levels of sectoral exports will be taken care of later.

### 3.1.4 Two Bayesian Models incorporating IO information

LeSage and Magura (1991) used the partial derivatives of these equations (although without the term for private consumption, thereby incorporating intermediate demand only) to calculate the response of each industry  $i$  to employment changes in industries  $j$ , thereby obtaining values for  $f_{ij}$ , the relative tightness of the variances around their prior means, which were chosen according to the random walk assumption. Partridge and Rickman (1998) used the complete definition of the partial derivatives (including final demands) to calculate their  $f_{ij}$ 's. Furthermore, in an alternative model, they used the elasticities  $\partial E_i / \partial E_j * E_j / E_i$  to specify prior means (in this case, they set the  $f_{ij}$  equal to unity).

Using information from the official Input Output table for Austria, compiled for the year 1995, and following the methodology described above, we set up an IO-BVAR, a Bayesian VAR with prior means according to inter-industry relationships. In chapter 3.2.1, the results from this model will be compared with those from an unrestricted VAR as well as from an M-BVAR, a BVAR utilizing the Minnesota prior.

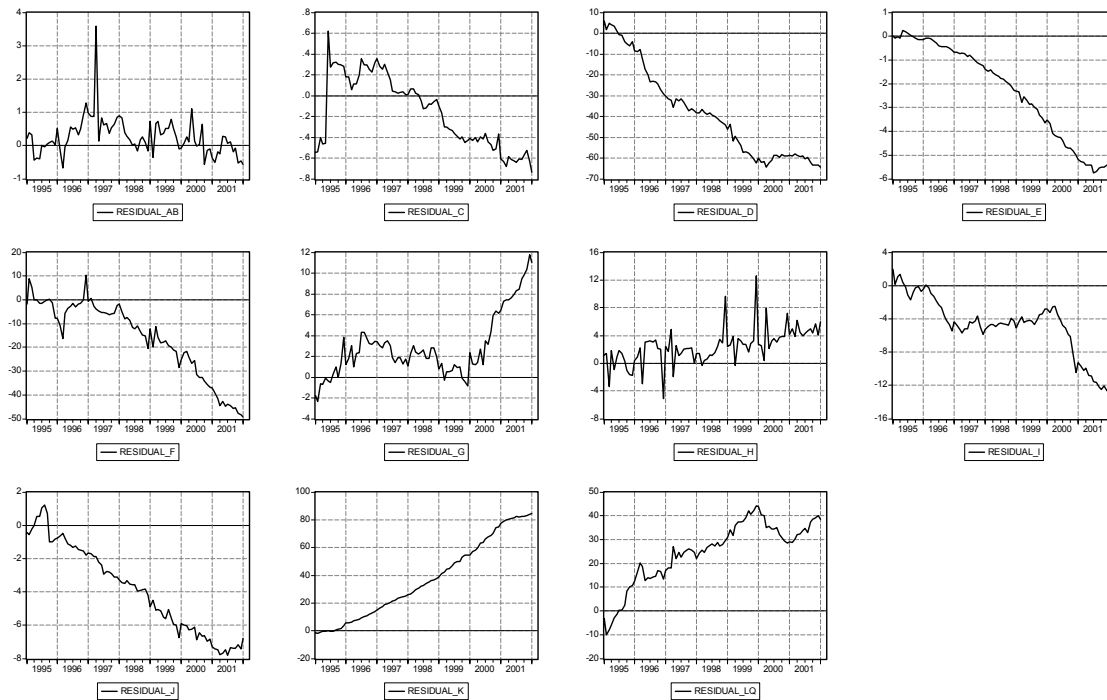
For our further analysis, however, we proceeded along somewhat different lines. In this, we set up a Bayesian VAR in differences, with Minnesota prior, but included an error correction term which is derived from the IO table in basically the same fashion as for the IO-BVAR. The idea is that in the short run, the employment series individually might exhibit random walk characteristics, while in the long run, structural interdependencies, as captured by the IO information, should feature more prominently.

The rationale behind the error correction term is the following: the most recent table is compiled for the year 1995, the starting year of the employment time series. Using average sectoral employment in 1995, together with the IO table, to derive numerical values for the wage rates, the productivities, and the ratios of final demand to wage income, the employment equations will hold, on average, for the year 1995.

In reality, sectoral linkages are constantly changing, due to changing methods of productions leading to changing input patterns, but also due to changes in the mix between domestically produced inputs and imported ones. IO tables, on the other hand, are static by nature, capturing the inter-industry relationships in just the year they are compiled for. This can be seen in the following Figure 3, where for each industry, the difference over time between the “hypothetical” level of employment, as derived from the equations above by using actual employment numbers for the right hand side variables, and the true level is depicted.

Clearly, the differences are not stable. Industries, whose share of total employment rises over time (see also Figure 2 above), exhibit positive and increasing residuals, whereas for shrinking industries, the reverse holds true. The size of these residuals can be substantial: at the end of the sampling period, the residual in sector K amounts to almost 85,000 employees, or about 31% of the total number.

Figure 3: Difference between real and hypothetical employment



Source: HVSV; own calculations

Now, this instability is due to the fact that the economic structure is evolving over time. We therefore attempted to model this evolution by means of a “dynamization” of the otherwise static IO relationships. In doing so, we pursued two approaches. One involved modelling the residuals with a quadratic time trend. The time trend, then, is supposed to pick up the changing structure of the inter-industry relationships. Deviations from this time trend, on the other hand, are thought to represent temporary effects which therefore might lend themselves to an error correction interpretation. For each industry, the “long-run” specification to be estimated was

$$E_i = \sum_{j=1}^n \psi_{ij} E_j + \beta_1 + \beta_2 t + \beta_3 t^2$$

In this equation,  $t$  is a time trend which in 1995:01 was set to 0. The first term on the right hand side is the (constant) level of employment corresponding to the IO table. To incorporate this structural information into a forecasting model, we constructed an Error Correction Model: a (Bayesian) VAR in differences is expanded to include the lagged residuals of the IO model. This model will be referred to as EC-BVART.<sup>5</sup> However, for this to be statistically appropriate, the residuals from the IO model must

<sup>5</sup> we tried this approach both within an unrestricted and a Bayesian VAR framework with Minnesota prior. With respect to forecasting performance, the “unrestricted” version of the EC-VAR turned out to be quite unsatisfactory. A Bayesian version of the model, however, performed much better. This Bayesian version in essence used the same lag structure, even the same hyperparameters as the the M-BVAR mentioned above; the inclusion of the lagged IO residuals constituted the only difference. In dealing with the residuals, we tried two options: one was to use an “informative prior” for the EC-coefficients (with a prior mean of -1, thereby inducing the model to react stronger to deviations from the IO equations). Much better results, however, were obtained by leaving the EC-coefficients unrestricted by using

be stationary. The residuals were therefore tested for stationarity by means of Augmented Dickey-Fuller tests (results see Appendix B). Most residuals appear to be stationary at least at the 5% level. The only sector which might pose problems is sector E (Electricity, Gas and Water Supply), whose residuals fail the ADF test even at the 10% level. When included in the EC-VAR, however, all residuals exhibit the correct negative sign, although a few are not significantly different from zero.

The second approach followed the same EC specification, but it went one step further by endogenising structural change itself. For each industry, a specification was chosen in which the coefficients relating employment in industry  $i$  to employment in industry  $j$  were allowed to vary over time. This time-variation was modelled with constant growth rates:

$$E_i = \sum_{j=1}^n \psi_{ij} (1 + \varepsilon_{ij})^t E_j$$

Due to the nature of this function, estimation has to be performed using non-linear methods. From month to month, the changes in the sectoral linkages should be small. Therefore, as a check on the results of these estimations, the parameters  $\varepsilon_{ij}$  should be (very) close to 0<sup>6</sup>. The residuals, which were again incorporated into an expanded BVAR as EC terms (this model is referred to as EC-BVARE), were subject to Augmented Dickey-Fuller tests (results see Appendix B). Again, most residuals appear to be stationary at least at the 5% level. Here, the sector which might pose problems is sector I (Transport, Storage, and Communications), whose residuals (albeit only slightly) fail the ADF test even at the 10% level. All residuals exhibit the correct negative sign in the EC-specification, again with a few of them not significantly different from zero (unsurprisingly, the least significant coefficient can be found for sector I).

Results from the Error correction models are presented in chapter 3.2.2 below.

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“uninformative priors” (technically, this is obtained by assigning very large prior variances to the respective coefficients). This leads to a substantial improvement in forecasting performance.

<sup>6</sup> A remark on the disappearance of the export term: exports are the one component of final demand which cannot plausibly be linked to the level of domestic employment, either directly by intersectoral linkages or indirectly via additional income. One way out would be to use time series of sectoral exports, which by assuming that in each sector, a homogeneous good is produced which is either exported or sold domestically, could be used to determine time series of the share of employment catering for exports. There are a number of problems with this approach, most important being those to do with the availability of the export data: historical values are available only with a considerable time lag of some 2 to 4 quarters. Additionally, in forecasting exercises, all sectoral exports would have to be forecast first.

Therefore, we eliminated the export term by assuming export shares which are constant over time. The time-varying parameters  $\varepsilon$ , then, have to pick up not only changes in inter-industry linkage patterns, but also these neglected changes in the levels and compositions of exports.

### 3.2 IMPLEMENTATION AND RESULTS

The results from our models are described in three sections: the first explores the forecast performance of the M-BVAR and IO-BVAR as compared to the performance of an unrestricted VAR<sup>7</sup>. The second presents the same comparison, but for the two error correction models. The third section, then, gives the results of a small forecast competition, which was carried out among 7 models: the two BVARs (M and IO), the two EC-VARs and the unrestricted VAR along with two single equation models, one consisting of ARIMA equations<sup>8</sup>, the other a naïve forecast where all future values are equal to the last in-sample observations<sup>9</sup>.

The results of the comparisons are presented as summary of the respective numbers of best and worst forecasts, at different forecasting horizons, for the models involved.

The hyperparameters of the Bayesian models were chosen with rather tighter variances on the cross terms (typically, in this kind of model, values of  $f_{ij}=0.5$  for  $i \neq j$  are commonly used). Moreover, for all models, a lag decay parameter of  $d=0$  was chosen (i.e., no lag decay was assumed). The EC-terms of models F and G as well as the prior means of model E were calculated from an IO employment model. Estimation was performed using EViews 4.0 (for the Bayesian estimation, a custom program performing mixed estimation was devised by the authors).

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<sup>7</sup> For all VARs, the viable lag length is restricted by the number of observations (at most 87, but only 60 for the shortest estimation sample) and the number of industries to be included in the model (11). Therefore, for reasons to do with degrees of freedom, it was not possible to contemplate lag lengths higher than 5; to prevent overfitting, not more than 3 were deemed sensible.

In the case of the unrestricted VAR, choosing the lag length according to forecasting performance resulted in the inclusion of only 2 lags. The VAR itself was set up in differences (for a classical VAR,  $I(1)$  variables should be estimated in differences; see e.g. Cromwell and Hannan (1993)).

The Bayesian VARs were also set up in differences (Although for a Bayesian VAR, e.g. Doan (2000) advised against differencing "in general". However, the forecasting performance of the BVARs in differences was appreciably superior to those in levels). The hyperparameters of the Bayesian VARs were selected using forecasting performance as well. The best results were obtained for a lag length of 3, with the values of the hyperparameters set at  $\theta = 0.1$  for the overall tightness,  $f_{ij} = 0.25$  for relative tightness, and no lag decay

<sup>8</sup> The ARIMA models were identified using the classical Box-Jenkins approach, utilizing the Autocorrelation and Partial Autocorrelation Functions to determine the number of AR and MA-terms (see, e.g., Pindyck and Rubinfeld, 1998). All series were differenced once (the results of Augmented Dickey-Fuller Tests hinted at all the series except one being integrated of order 1, the exception being sector 1, agriculture, which appeared to be stationary).

<sup>9</sup> These are derived from the simple model  $X_{t+i} = X_t$ ,  $i = 1, 2, 3, \dots$ , i.e., all future values are the same and equal to the last observation. In a true random walk model, the naïve forecast model would be optimal.

### 3.2.1 Performance of the Bayesian VARs

As the “reference model” for the BVARs, an unrestricted VAR was chosen. Description of the models in this comparison:

- VAR: unrestricted VAR (in differences) with 2 lags
- M-BVAR: a Minnesota-type Bayesian VAR with 3 lags ( $\theta=0.10$ ,  $f_{ij}=0.25$   $i \neq j$ )
- IO-BVAR: a Bayesian VAR with 3 lags, whose prior means were derived from an IO table ( $\theta=0.20$ ,  $f_{ij}=0.25$   $i \neq j$ )

The results are as follows:

Model-Type	# best forecasts					# worst forecasts				
	total	1-6	7-12	13-18	19-24	total	1-6	7-12	13-18	19-24
VAR	57	10	15	14	18	187	52	48	44	43
M-BVAR	121	38	34	29	20	60	10	13	15	22
IO-BVAR	86	18	17	23	28	17	4	5	7	1

With a very small share of worst forecasts – and a very reasonable share of best forecasts – the IO-BVAR seems to dominate the other two approaches; this is especially true for longer horizons: in the 19-24 steps ahead interval, it has a single instance of worst forecasts, but a more than 40% share of best forecasts (up from 27% for the short run 1-6 steps ahead interval). Conversely, the M-BVAR can compete only for forecast horizons of up to about 12 months. The unrestricted VAR is more consistent: it displays a share of more than 2/3 of worst forecasts for all forecast horizons.

### 3.2.2 Performance of the EC-BVARs

Again, the EC-BVARs were referenced against the unrestricted VAR. The model details are as follows:

- VAR: unrestricted VAR (in differences) with 2 lags
- EC-BVAR<sub>t</sub>: an EC-BVAR with 3 lags using residuals from the IO model with quadratic trend ( $\theta=0.10$ ,  $f_{ij}=0.25$   $i \neq j$ )
- EC-BVAR<sub>e</sub>: an EC-BVAR with 3 lags using residuals from the IO model with time-varying coefficients ( $\theta=0.10$ ,  $f_{ij}=0.25$   $i \neq j$ )

And here are the results:

Model-Type	# best forecasts					# worst forecasts				
	total	1-6	7-12	13-18	19-24	total	1-6	7-12	13-18	19-24
VAR	95	18	20	27	30	34	24	7	2	1
EC-BVAR <sub>t</sub>	77	22	22	15	18	104	20	26	28	30
EC-BVAR <sub>e</sub>	92	26	24	24	18	126	22	33	36	35

In this contest, it is the unrestricted VAR which dominates most periods. Apart from the 1-6 step ahead period, where the two EC-BVARs seem to do equally well (and a little better than the VAR), the Input Output models look like a poor choice. For a discussion of the reasons behind this result and the steps which could be taken for its remedy, please visit the last chapter 4, *Conclusions and Outlook*.

### 3.2.3 A small “M”-competition

In order to provide an even more comprehensive evaluation of the forecasting performance, an exercise was undertaken to compare the results from the aforementioned multi-variable models with those of two single variable models, a “naïve” model and an ARIMA model.

The 7 models entering the competition were:

- A* the naïve model
- B* single equation ARIMA,
- C* an unrestricted VAR with 2 lags,
- D* a Minnesota-type Bayesian VAR with 3 lags ( $\theta=0.10$ ,  $f_{ij}=0.25$   $i \neq j$ )
- E* a Bayesian VAR with 3 lags, whose prior means were derived from an IO table ( $\theta=0.20$ ,  $f_{ij}=0.25$   $i \neq j$ )
- F* an EC-BVAR with 3 lags using residuals from the IO model with quadratic trend ( $\theta=0.10$ ,  $f_{ij}=0.25$   $i \neq j$ )
- G* an EC-BVAR with 3 lags using residuals from the IO model with time-varying coefficients ( $\theta=0.10$ ,  $f_{ij}=0.25$   $i \neq j$ )

The hyperparameters of the Bayesian models were chosen with rather tighter variances on the cross terms (typically, in this kind of model, values of  $f_{ij}=0.5$  for  $i \neq j$  are commonly used). Moreover, for all models, a lag decay parameter of  $d=0$  was chosen (i.e., no lag decay was assumed). The EC-terms of models F and G as well as the prior means of model E were calculated from an IO employment model. Estimation was performed using EViews 4.0 (for the Bayesian estimation, a custom program performing mixed estimation was devised by the authors).

Detailed forecasting results for the 7 models and the 3 forecast horizons, 1, 12, and 24 steps ahead, are listed in Appendix B.

Model	type	# best forecasts					# worst forecasts				
		total	1-6	7-12	13-18	19-24	total	1-6	7-12	13-18	19-24
<b>A</b>	<i>naïve</i>	<b>60</b>	12	15	19	14	<b>26</b>	7	6	6	7
<b>B</b>	<i>ARIMA</i>	<b>35</b>	11	9	6	9	<b>1</b>	0	0	0	1
<b>C</b>	<i>VAR</i>	<b>5</b>	1	1	1	2	<b>33</b>	24	7	2	0
<b>D</b>	<i>M-BVAR</i>	<b>39</b>	15	12	9	3	<b>11</b>	0	3	2	6
<b>E</b>	<i>IO-BVAR</i>	<b>45</b>	10	7	11	17	<b>5</b>	0	1	4	0
<b>F</b>	<i>EC-BVAR<sub>t</sub></i>	<b>54</b>	14	15	13	12	<b>108</b>	19	29	30	30
<b>G</b>	<i>EC-BVAR<sub>e</sub></i>	<b>26</b>	3	7	7	9	<b>80</b>	16	20	22	22

As a summary of forecast performance, Table 1 provides for each model and forecasting period the number of the best and worst sectoral forecasts. The naïve model, although scoring top in the number of best forecasts, is only a good average when worst forecasts are concerned. Over all 4 forecasting periods, the best forecasts are fairly evenly spread out about the models, the exception being the unrestricted VAR and, for the shorter periods, the time-varying EC-BVAR<sub>e</sub>. Nevertheless, according to the number of worst forecasts, the VAR does a much better job than the EC-BVAR<sub>e</sub>. The two Error Correction models perform very poorly indeed: for longer forecast horizons, between them they share

the blame for most of the worst forecasts, despite their fair number of best forecasts (here, the EC-BVARt comes out second<sup>10</sup>). What is even more disturbing is the fact that their performance gets worse the longer the forecast horizon. This fatally undermines the hope that their incorporation of structural information might lead to improved forecasts especially in the long run.

Nevertheless, information from Input Output models is not useless at all: with an above-average share in the number of best and a negligible number of worst forecasts, the IO-BVAR model (which furthermore seems to bear out the proposition that IO information should improve forecasting accuracy especially for longer horizons) can be declared winner of this limited forecasting competition, with the single equation ARIMA model a close second. A little behind, the Minnesota-type M-BVAR's performance might also be considered reasonable. As already mentioned, the naïve forecasts score very well when best forecasts are concerned, although the fact that they are widest of the mark in an unacceptable number of instances renders them less than recommendable. As for the last remaining model, a combination of a low number of best and a high number of worst results makes the VAR look like a rather inferior choice.

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<sup>10</sup> a comparison of the results of the "M"-competition with the 3 model-contests above reveals a drawback of the "best-and worst forecast" tables: from the results of chapter 3.2.2, *Performance of the EC-BVARs*, the two EC-BVARs would have been judged about equal in forecasting performance. This chapter's results, on the other hand, would hint at the EC-BVARt being quite superior to the EC-BVARE. The reason is, of course, the larger number of models in this chapter, where other models stand a chance to grab the title of "best forecast" in sectors where the EC-BVARE performs better than the EC-BVARt. Therefore, to really give a fair chance to each of the models, a more exhaustive "voting scheme" should be used.

## 4 Conclusions and Outlook

In a nutshell, is it worthwhile to bother with Input Output tables when trying to forecast sectoral employment? The answer seems to be a qualified “Yes”. In a Bayesian framework, inter-industry relationships can, at least in the case of Austria, modestly but appreciably improve forecast accuracy, even more so for longer horizons than for shorter ones. The approach involving Error Correction mechanisms derived from IO tables, however, seems less promising.

Nevertheless, even this last, rather disappointing, result comes with a slight caveat: for shorter forecast horizons, the EC-BVARs (and especially the trend-modelled EC-BVART) seem to perform rather better (or is less bad?) than for longer horizons. This might hint at the possibility that it is less the Error Correction mechanism in principle, but rather the way it has been operationalised in the present study. The quadratic time trend, which was used in the more successful of the two EC-models, certainly has substantial drawbacks when extrapolated too far into the future, as its deterministic nature conceivably is prone to wandering ever wider from the “true” development of the underlying inter-industry relationships. On the other hand, the time-varying coefficients which were used for the alternative EC-model, as modelled in this study, can pose substantial numerical problems, as the parameters which have to be estimated are very close to zero. Additionally, as the Error Correction mechanism is constructed, they enter the model being raised to the power of a time variable, which also hints at the distinct possibility that as it is farther projected into the future, even small estimation errors become unduly influential.

Lastly, the sectoral composition of the industries as chosen in the present paper might be less than optimally chosen; especially the lumping together of sectors L to Q seems questionable<sup>11</sup>. Sector L, for example, consists of workers in the public sector and defence. Its size therefore depends heavily on official policy, although its slight expansion over the last 7 years is somehow at odds with the professed commitment of various governments to slim down the public sector. Nevertheless, it might be reasonable to remove this sector from the models. As preliminary work shows, when this sector is treated as exogenous in forecasts, this leads to a substantial improvement in the results of the remaining sectors. A similar problem is posed by sector A/B, Agriculture, Forestry, and Fisheries, which is heavily dominated by small, self-employed farmers; the reduction in their number far exceeds the reduction in agricultural wage employment. As a last idea, the manufacturing sector D might better be broken up in two subsectors (or even three, although care has to be taken to keep the number of sectors within reasonable limits).

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<sup>11</sup> The sectoral aggregates in this paper are chosen for reasons to do with the authors’ occupational duties: since last year, we had a string of assignments from regional governmental agencies to construct forecasts of regional employment on a sectoral basis. The 11 sectors of this study conform to the (crudest) level of detail we have to come with for these assignments



## Appendix A: Mean Absolute Percentage Errors

1 step-ahead												
	Industry											
	ab	c	d	e	f	g	h	i	j	k	lq	t
naive	1.14	0.43	0.12	0.30	0.58	0.18	1.04	0.27	<b>0.16</b>	0.49	<b>0.11</b>	0.12
ARIMA	1.07	0.47	<b>0.09</b>	0.31	0.59	0.17	1.00	0.27	0.16	0.35	0.15	0.12
VAR	2.02	1.02	0.14	0.32	1.01	0.23	1.90	0.38	0.25	0.38	0.22	0.15
M-BVAR	1.11	0.43	0.12	<b>0.27</b>	0.57	0.17	0.99	<b>0.27</b>	0.17	<b>0.31</b>	0.16	0.12
IO-BVAR	1.14	<b>0.41</b>	0.12	0.29	0.59	<b>0.16</b>	1.01	0.29	0.19	0.32	0.18	0.12
EC-BVARt	<b>1.02</b>	0.75	0.13	0.35	<b>0.55</b>	0.22	<b>0.84</b>	0.32	0.20	0.39	0.18	<b>0.11</b>
EC-BVARE	1.22	0.44	0.13	0.27	0.80	0.19	0.89	0.33	0.19	0.39	0.19	0.15

12 steps-ahead												
	Industry											
	ab	c	d	e	f	g	h	i	j	k	lq	t
naive	1.35	2.28	<b>0.82</b>	2.38	4.10	1.04	1.59	2.00	<b>0.17</b>	5.39	<b>0.58</b>	0.41
ARIMA	<b>0.88</b>	2.52	1.00	1.18	2.99	0.70	1.23	1.95	0.17	3.57	0.79	0.86
VAR	1.78	<b>1.37</b>	1.07	1.22	1.88	0.79	2.08	2.39	0.39	2.47	0.95	0.45
M-BVAR	1.11	1.53	1.20	1.03	3.13	0.70	0.89	<b>1.90</b>	0.38	2.13	0.69	0.33
IO-BVAR	0.98	1.39	1.20	<b>1.01</b>	3.07	0.68	0.97	2.10	0.38	2.20	0.85	0.47
EC-BVARt	2.71	2.66	1.15	2.38	<b>0.67</b>	1.38	<b>0.69</b>	2.98	0.65	<b>2.06</b>	0.72	<b>0.25</b>
EC-BVARE	2.07	1.75	0.97	1.14	6.05	<b>0.58</b>	1.62	3.49	0.49	3.50	1.47	1.42

24 steps-ahead												
	Industry											
	ab	c	d	e	f	g	h	i	j	k	lq	t
naive	1.19	4.39	0.80	4.56	7.99	1.69	4.24	<b>3.65</b>	0.22	10.60	<b>0.39</b>	0.42
ARIMA	1.19	4.39	0.96	1.16	7.18	<b>0.56</b>	3.38	4.16	<b>0.22</b>	5.86	2.94	2.33
VAR	3.99	4.46	1.13	1.10	3.23	0.85	2.58	4.95	0.53	1.69	2.86	1.08
M-BVAR	<b>0.79</b>	3.04	1.66	<b>1.06</b>	6.42	0.80	2.69	3.87	1.09	1.60	2.40	0.78
IO-BVAR	0.92	<b>2.89</b>	1.42	1.10	6.01	0.59	2.65	4.28	0.82	<b>1.28</b>	2.70	1.03
EC-BVARt	7.08	7.30	1.05	4.94	<b>1.83</b>	2.90	<b>1.64</b>	6.27	1.88	1.77	1.65	<b>0.14</b>
EC-BVARE	3.99	3.42	<b>0.67</b>	3.16	10.55	1.06	3.25	8.67	1.52	6.96	4.75	4.02

rem.: **bold** numbers indicate least errors, *italics* indicate worst errors.

## Appendix B: ADF-Tests of Long Run Residuals

quadratic trend-model:

### Augmented Dickey-Fuller Tests (1995:01 - 2002:03)

<i>Industry</i>	ADF-Statistic	# lags	sign. <sup>1</sup>
<b>A/B</b> <i>Agriculture, Hunting and Forestry, Fishing</i>	-3.50	2	***
<b>C</b> <i>Mining and Quarrying</i>	-2.65	1	***
<b>D</b> <i>Manufacturing</i>	-2.14	2	**
<b>E</b> <i>Electricity, Gas and Water Supply</i>	-0.66	3	
<b>F</b> <i>Construction</i>	-3.70	2	***
<b>G</b> <i>Wholesale and Retail Trade, Repair of Motor Vehicles</i>	-2.12	2	**
<b>H</b> <i>Hotels and Restaurants</i>	-5.99	2	***
<b>I</b> <i>Transport, Storage and Communications</i>	-1.70	3	*
<b>J</b> <i>Financial Intermediation</i>	-3.75	1	***
<b>K</b> <i>Real Estate, Renting, Business Related Services</i>	-3.17	4	***
<b>L-Q</b> <i>Public Administration, Education, Health, Other pers. Services</i>	-2.34	1	**

<sup>1</sup> \*\*\* ... significant at the 1% level  
 \*\* ..... 5% level  
 \* ..... 10% level

time-varying parameter model:

### Augmented Dickey-Fuller Tests (1995:01 - 2002:03)

<i>Industry</i>	ADF-Statistic	# lags	sign. <sup>1</sup>
<b>A/B</b> <i>Agriculture, Hunting and Forestry, Fishing</i>	-2.56	3	**(*)
<b>C</b> <i>Mining and Quarrying</i>	-3.05	2	***
<b>D</b> <i>Manufacturing</i>	-2.33	2	**
<b>E</b> <i>Electricity, Gas and Water Supply</i>	-1.84	3	**
<b>F</b> <i>Construction</i>	-1.86	2	*(*)
<b>G</b> <i>Wholesale and Retail Trade, Repair of Motor Vehicles</i>	-2.74	2	***
<b>H</b> <i>Hotels and Restaurants</i>	-5.98	2	***
<b>I</b> <i>Transport, Storage and Communications</i>	-1.60	3	(*)
<b>J</b> <i>Financial Intermediation</i>	-4.76	1	***
<b>K</b> <i>Real Estate, Renting, Business Related Services</i>	-3.49	4	***
<b>L-Q</b> <i>Public Administration, Education, Health, Other pers. Services</i>	-2.53	1	**(*)

<sup>1</sup> \*\*\* ... significant at the 1% level  
 \*\* ..... 5% level  
 \* ..... 10% level

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