THE DEVELOPMENT OF REGIONAL EMPLOYMENT IN GERMANY: RESULTS FROM NEURAL NETWORK EXPERIMENTS

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Abstract

This paper offers an overview of experimental results, based on neural networks (NNs) used to forecast regional employment variations in Germany. In this context, NN models which provide forecasts two years ahead have been developed. NNs are statistical optimization tools inspired by the functioning of biological neural networks. Their main characteristics are their non-linear and multiple-unit simultaneous data processing, as well as their ability to find functional relationships within the data without these relationships being previously specified.
The present paper – after a brief introduction and a methodological review of NNs – presents the results, for a set of NN models, of their application to regional data concerning full-time employment in Germany. The database used in our experiments consist of two panels of 326 and 113 NUTS 3 districts, which represent West and East Germany, respectively. Since the data sets display different time spans, West and East German NN models were developed separately. First, two years, 2001 and 2003, were used to test the models' statistical performance, based on single estimates of employment growth rates computed for each German district. Next, additional – and more recent – forecasts are presented, for the years 2004, 2005, and 2006. New NN models, embedding shift-share analysis components, are also adopted and evaluated, by means of appropriate statistical indicators and GIS map visualisations. The paper concludes with theoretical/methodological/empirical observations in the light of future research developments.

1. Neural Networks for Forecasting Employment in Germany: A Brief Introduction

An increased demand for meso-economic (sectoral or regional) forecasts has been observed over the years (for a discussion of the importance of forecasting, see, among others, Daub 1984). However, such increased forecasting needs also create new problems, such as: a) the greater disaggregation at which economic data are collected, which generates an imbalance between the number of regional figures to be forecasted and the quantity of observations available over time; and b) the difficulties of studying the complex dynamic interdependencies that influence economic trends and cycles. Next to traditional statistical-economic tools we witness nowadays a rising popularity of statistical learning techniques. The family of methods termed neural networks[1] (NNs) provides an approach to forecasting that is alternative to conventional econometric techniques. NNs are able to overcome some of the aforementioned problems because of non-linear statistical optimization algorithms (see, for example, Cheng and Titterington 1994). In particular, the NNs' capacity to learn from the data and of finding (unknown) functional relationships between variables is what makes them a flexible statistical tool for the solution of complex problems.

NNs do not require an a priori study of the estimation function, nor a specification process for the set of regressors employed. On the one hand, their no-modelling hypothesis is an impediment for a clear economic (or other) interpretation. On the other hand, the limited possibilities of interpretation of the results is less relevant when the aim, as in our case, is to forecast, rather than to explain the relationship between the factors. Analysts from diverse fields are interested in NNs because of their simple approach, and a great number of NN applications can be found in the recent literature (for a review of the use of NNs in forecasting, see, for example, Zhang et al. 1998). A wide literature is also available that draws comparisons between NNs and conventional statistical methods (see, amongst others, Cheng and Titterington 1994; Swanson and White 1997a, 1997b; Baker and Richards 1999; Sargent 2001). In the labour field, NNs have been employed in the study of labour productivity (Sonmez and Rowings 1998; Lu et al. 2000), or in the analysis of market segmentation (Gaubert and Cottrell 1999). Longhi et al. (2005a; 2005b) studied the application of NNs in a panel and cross-sectional data framework. However, the evaluation of the effectiveness of NNs shows quite some variety in the literature, as different authors have either made positive observations (Swanson and White 1997b; Adya and Collopy 1998) or have come to negative conclusions (Stock and Watson 1998).

Formally, NNs can be defined as systems of units (or 'neurons') that are distributed in layers. In 'feedforward' NNs, the information computed by the NN is passed forward from layer to layer by means of connections between units. The first layer contains the model's input, while the last one contains the output. Intermediate ('hidden') layers enable additional computations. In Fischer (2001b, p. 23), a processing unit u_i, belonging to $\boldsymbol{u} = \{u_1,...,u_k\}$ is defined as:

$$u_i = \varphi_i(\boldsymbol{u}) = \Im_i\left(f_i(\boldsymbol{u})\right), \tag{1}$$

where $\Im_i$ is an activation function, which computes each unit's output, while f_i is an integrator function, which is used for aggregating the output from the preceding layer. This is usually done by means of a linear (weighted) combination of the inputs. The recursive modification of the weights used in the integrator function guarantees the 'learning process' of an NN. The backpropagation algorithm (BPA) (for details, see Rumelhart and McClelland 1986) is commonly used for this task, and is therefore employed in the experiments presented in this paper. In the BPA, input examples and their correct (known) outputs need to be provided. NN models that follow this kind of process are called 'supervised' NNs. On the basis of the sample data, the NN models can identify the behaviour underlying the data and, subsequently, replicate it for out-of-sample forecasts.

In this paper, we are concerned with the use of NNs in order to forecast regional employment variations and, particularly, the evolution of labour markets in Germany. In this context, the focus is, therefore, not on the use of NN algorithms per se, but on their application to panel and cross-sectional data.[2] Contributions on NNs that deal with panel data are rare (see Lin 1992), since these are usually analysed by means of various conventional estimation techniques (examples for the case of German labour markets can be found in Blien and Tassinopoulos 2001; Bade 2006). Our experiments focus on short-term employment forecasts, that is, forecasts 2 years ahead, at the regional level. The high number of cross-sections in the data analysed and the limited number of years for which data are available represent problematic issues for conventional econometric techniques. This is where NN techniques can be of help. We develop and study a set of NN models, and review their statistical results.

The analysis of the NN performance is carried out following the rules defined by Collopy et al. (1994), who suggest: 1) the comparison of the NN statistical performance with that of widely-accepted conventional models, such as a random walk; and 2) the test of the NN models' out-of-sample performance. In addition to these general validation rules, the implementation of the NN models must adhere to an additional set of procedures, defined in Adya and Collopy (1998): a) provision of the in-sample performance of the NN models, which is a benchmark for the evaluation of the generalization properties of the NN models;[3] and b) observation of the stability of the NNs' statistical performance over different data sets, which enables the assessment of their stability and reliability as a forecasting tool.

The rest of the paper is organized as follows. Section 2 describes the data used in our experiments. Section 3 first explains the practical steps in the implementation of the NN models, subsequently reviewing the statistical results of the empirical application, which aims to estimate employment variations in West and East Germany for the years 2001 and 2003. Section 4 presents additional results obtained on more recent data. *Ex post* forecasts for the year 2004 are evaluated, followed by forecasts carried out for 2005 and 2006. In this latter context, new NN models, embedding shift-share analysis (SSA) components, are also adopted and evaluated by means of appropriate statistical indicators and map visualisations. Finally, Section 5 draws some conclusions and sets future research directions.

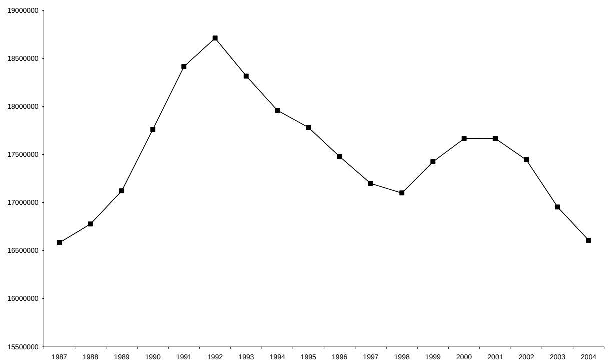
2. The Data

The experiments presented in this paper were carried out at the regional scale, at the so-called NUTS 3[4] level of geographical data aggregation. This classification corresponds, in Germany, to district units (*kreise*). The main data set employed in our experiments concerns full-time employees, is provided by the German Institute for Employment Research (Institut für Arbeitsmarkt und Berufsforfschung, IAB), and collected, for social security purposes, by the (German) Federal Employment Services (Bundesanstalt für Arbeit, BA). As these data are directly collected for administrative purposes and at single-firm level, they are expected to have rather low and non-systematic measurement errors.

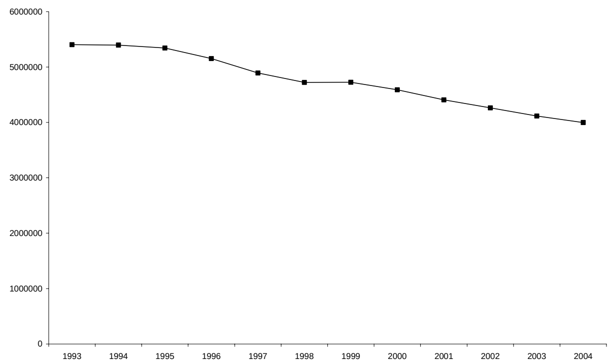
The data used in our experiments are drawn from quarterly statistics, and they refer to 30 June, for each year observed. However, the time span of the data for West and East Germany is different. The West German data cover 18 years (1987–2004), while the East German data are only available for 12 years (1993–2004). Because of the different time spans of the data, there is a chance to use a longer data set in forecasting West German employment, instead of using the same number of years as for East Germany. Our choice was for the former approach, which employs the full set of information available.

At the NUTS 3 disaggregation level, the number of districts to be analysed is 326 for West Germany and 113 for East Germany, amounting to a total of 439. In practical terms, we have two data sets, organized as panels of observed regions. In addition, the employment data are classified according to nine economic sectors.[5] Figure 1 shows the aggregate trends of West and East German full-time employment for the period considered.

The graph for West Germany shows a post-unification decline of employment, followed by a late-1990s revival, and a recent fall. On the other hand, the graph for East Germany displays a constant decrease of full-time employment in the area. In detail, Figure B.1 in Annex B shows the most recent employment variations in Germany, for the 2002–04 period.



a)



b)

Figure 1 – Aggregate full-time employment trends: a) West Germany (1987–2004); b) East Germany (1993–2004)

Further variables were used in our experiments. Average per-district daily wages earned by full-time workers are also available for the same period as the employment data, with the exception of the year 2004. We also employ a 9-point district classification system, which includes information on the 'type of economic region' analysed.[6] The data set illustrated here was employed in our forecasting experiments, which will be described in Sections 3 and 4.

3. Empirical Application of Neural Network Models to Labour Markets in West and East Germany

3.1 Implementation of the Neural Networks Adopted

In order to evaluate the usefulness of an NN forecasting model, it is first necessary to explain its structure and implementation. Therefore, this section will illustrate the various NN models developed for our forecasting purposes.

Our models, initially presented in Patuelli et al. (2003) employ, as the main input variable, the regional growth rates of full-time workers, for the nine economic sectors. The NN forecasting models developed for our experiments compute 2-year-ahead forecasts. Consequently, the growth rates of the explanatory variables (sectoral employment and, if applicable, daily wages) were computed for the previous period, (t–2, t).

Most NNs do not explicitly handle time. Consequently, the correlation of observations over time has to be introduced, in our model, through what we indicate as the 'time' variable. This variable was employed in two formats. First, we introduced a time variable that can be interpreted as a 'fixed effects' variable in panel models.[7] As an alternative specification, we used time as a set of dummy variables – one for each year. Our models employ additional variables, in addition to the time variable, in order to enrich their forecasting power. On the basis of two basic models, Model A (time as dummies) and Model B (time as 'fixed effect'), five additional extended NN models were developed (see Table 1, or, for more details, Patuelli et al. 2006):

- Model AD has the same inputs as Model A, in addition to the variable 'type of economic region'. As in the case of the fixed effects variable for time, this can be seen as the NN equivalent of cross-sectional fixed effects in a panel model (Longhi et al. 2005a).

- Furthermore, Model B was also improved with the variable 'type of economic region', thereby obtaining Model BD.

Finally, data on regional average daily wages are used as an input variable:

- a) in Model A, obtaining Model AW;
- b) in Model AD, obtaining Model ADW; and
- c) in Model B, obtaining Model BW.

Table 1 – Description of the input variables employed in the NN models

Model	*Input variables*
A-type models	
Model A	Growth rate of sectoral employment; time dummies
Model AD	Growth rate of sectoral employment; time dummies; type of economic region fixed effects
Model ADW	Growth rate of sectoral employment; time dummies; type of economic region fixed effects; growth rate of daily wages
Model AW	Growth rate of sectoral employment; growth rate of daily wages; time dummies
B-type models	
Model B	Growth rate of sectoral employment; time fixed effects
Model BD	Growth rate of sectoral employment; time fixed effects; type of economic region fixed effects
Model BW	Growth rate of sectoral employment; time fixed effects; growth rate of daily wages;

For practical purposes, the families of NN models employing time as dummies or as fixed effects will from now on be referred to as A-type or B-type models, respectively.

3.1.1 The Neural Network Configuration and Testing

In order to define each NN model's structure, in terms of number of layers and – possible – hidden units, several configurations have been tested in a first phase (referred to as the validation phase).[8] The process of choice of the NN structure is, indeed, a critical one, as a balance between simplicity and complexity of the network must be found. An NN that is too simple will not able to find complex relationships between the variables, resulting in smoothed-out forecasts (see Fischer 2001a). On the other hand, a overly-complex NN would have little generalization power, because of data overfitting. One solution for this particular problem is an early stopping of the training, once the evaluation of the network's performance shows a deterioration.

The above NN models were validated using data until the year 2000. The models' performance was evaluated by means of a set of statistical indicators,[9] and the best-performing settings were then chosen for further use. The out-of-sample performance of the NN models was tested by *ex post* forecasts carried out for the years 2001 and 2003.[10] Multiple out-of-sample forecast years make it possible to observe the stability of the forecasts over time and different values, while the observation of the average performance of the NNs (as computed for the years 2001 and 2003 in our case study) may reduce the influence of possible region- or time-specific shocks.

The results of such forecasts are presented in the next two subsections. Section 3.2 presents the results of the NN models developed for forecasting employment in West Germany, while Section 3.3 does the same for East German employment forecasting. Finally, Section 3.4 will discuss NN models' evaluation methodologies, such as Multi-Criteria Analysis (MCA) or rank order analysis.

3.2 Results for West Germany for the Years 2001 and 2003

Seven NN models were used to forecast employment variations in West Germany. Two-year-ahead forecasts (t+2) were performed for two periods, 1999–2001 and 2001–03, in order to compare the NNs' *ex post* forecasts on two different sets of data. In order to obtain our forecasts, we trained the NN models up to the years 2000 and 2002, respectively, while the years 2001 and 2003 were the test sets. The average statistical indicators emerging from the 2001 and 2003 experiments are presented in Table 2. The computation of the average results for two test sets provides a more reliable assessment of the performance of the NNs. The table also presents the average results obtained for the in-sample performance of the models, that is, the indicators computed on the training data.

Table 2 – Average statistical performance of the *ex post* forecasts for the years 2001 and 2003: the case of West Germany

Indicator	*Model A*	*Model AD*	*Model ADW*	*Model AW*	*Model B*	*Model BD*	*Model BW*
				In-sample performance			
MSE	6434988	5804853	7728190	7372714	26002864	24088980	30845880
MAE	1366.59	1313.14	1498.10	1454.90	2671.30	2656.40	2908.91
MAPE	2.2223	2.1213	2.3767	2.3133	3.9902	4.0430	4.3292
				Out-of-sample performance			
MSE	20813437	36811629	23468487	29222080	8395425	8913146	7369825
MAE	2183.24	3033.47	2674.87	2741.00	1624.39	1643.27	1513.61
MAPE	3.5393	5.0899	4.9141	4.9173	2.9819	2.8674	2.7663
Theil's U	1.1577	2.2083	1.4969	1.8401	0.4722	0.5109	0.4079

On the basis of the results presented in Table 2, a few observations should be made. First, a significant difference can be seen in the statistical performance of the A-type and B-type models. The three B-type models – employing time fixed effects – show lower out-of-sample forecasting errors in every statistical indicator. Also, the out-of-sample performance of the A-type models – employing time dummies – is worse than their in-sample performance, seemingly indicating data overfitting, and a consequently weak generalization. In contrast, for the B-type models we can observe greater generalization properties. Finally, we can not find a unique winning model. On the other hand, the B-type models have the lowest error for all the indicators computed. Also, according to Theil's U statistic, the B-type models largely overcome a no-change-hypothesis random walk, while several of the A-type models do not. Outperforming simpler, naïve forecasting models such as random walk is, as stated in Section 1, a minimum condition for the acceptance of a new forecasting methodology.

Synthesizing, we might conclude that, although the values of the statistical indicators are the result of only 2 years being averaged, the B-type models seem to outperform the A-type models. These results are encouraging when compared with further detailed experiments (Longhi 2005). Longhi carries out one-step-ahead employment forecasts for West Germany by means of NNs, finding that, though better than traditional panel methods, the B-type models only slightly win over the naïve no-change random walk. Vice versa, the B-type (t+2) models adopted in this analysis largely outperform a no-change random walk, generating only about half the error emerging from the random walk model.

Next, by considering the aggregate level, the regional forecasts obtained by the two families (A- and B-type) of NN models generate different forecasts (Figure 2) for the year 2003. In particular, the models belonging to each family seem to cluster together in 2003, suggesting a common pattern of forecasts, which also settles nearer to the actual values to be forecasted. This tendency to clustering of similar models is sound and could also have been hinted at from the statistical performance of NN models, seen in Table 2.

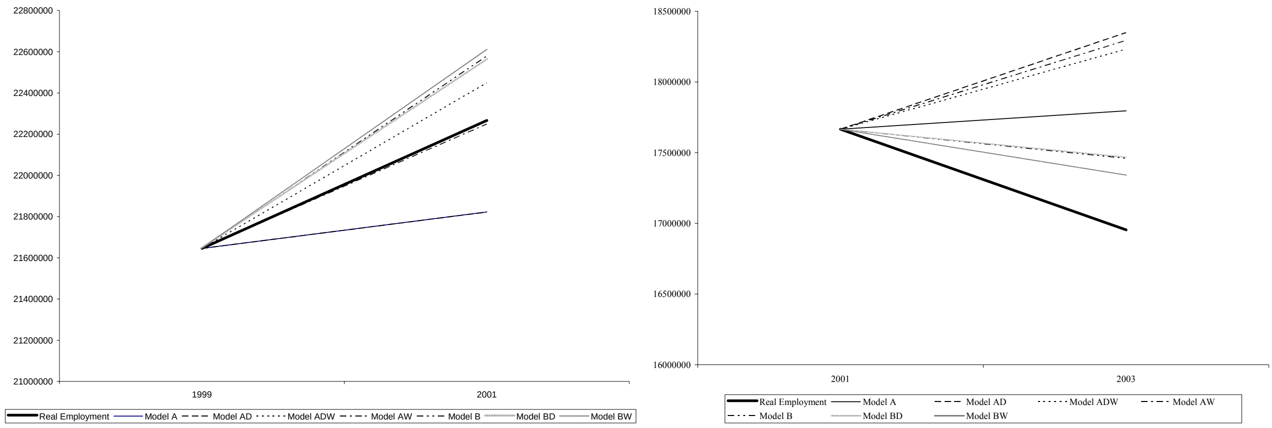


Figure 2 – Aggregate NN forecasts for the years 2001 (left) and 2003 (right): the case of West Germany

The subsequent section will present the results obtained when forecasting employment variations for East Germany, by utilizing the same type of NN models as in the case of West Germany. Also, the NN models evaluation procedure will be carried out in the same way as for West Germany.

3.3 Results for East Germany for the Years 2001 and 2003

In this section, we illustrate – for the case of forecasting employment variations in East Germany – the results of the statistical performance of the NN models adopted for the case of West Germany. The data set used for East Germany covers employment in East Germany’s 113 NUTS 3 districts, from 1993 to 2003. The period for which the data are available is therefore shorter than it is for West Germany, which might imply less accurate forecasts. This would be true if the information on the early years had a significant influence on the positive performance of the NNs.[11] As for the case of West Germany, the NN models carried out *ex post* forecasts for both the 1999–2001 and 2001–03 periods. Table 3 illustrates the statistical indicators computed – on average – on the aforementioned NN models.

Concerning the statistical performance of the NN models, Table 3 shows slightly less homogeneous results than Table 2. However, Table 3 shows that, as in the case of West Germany, the B-type models outperform the A-type models, which only seem to be competitive when the error is computed as MAPE. Further, the A-type models are often outperformed by the random walk model in terms of MSE.

The same trends observed at regional level can be seen at the aggregate level (Figure 3). Concerning the year 2003, the B-type models are those which better approximate the observed employment change, while the A-type models provide more optimistic values, though still with negative growth.

Table 3 – Average statistical performance of the *ex post* forecasts for the years 2001 and 2003: the case of East Germany

Indicator	*Model A*	*Model AD*	*Model ADW*	*Model AW*	*Model B*	*Model BD*	*Model BW*
				In-sample performance			
MSE	18113891	8581342	21062596	18693695	24641753	23318896	23611197
MAE	1688.69	1545.30	1799.66	1728.76	1829.47	1826.50	1680.73
MAPE	3.5358	3.5869	3.6919	3.6169	3.7298	3.7496	3.4063
				Out-of-sample performance			
MSE	11735072	22200869	21108442	32489364	5760466	5504239	6816745
MAE	1534.36	2147.65	1712.01	1598.35	1312.86	1370.54	1502.80
MAPE	3.9248	5.5472	4.1054	3.3474	3.6260	3.8070	4.0034
Theil's U	0.8892	0.9954	1.2933	2.9720	0.5940	0.5501	0.5177

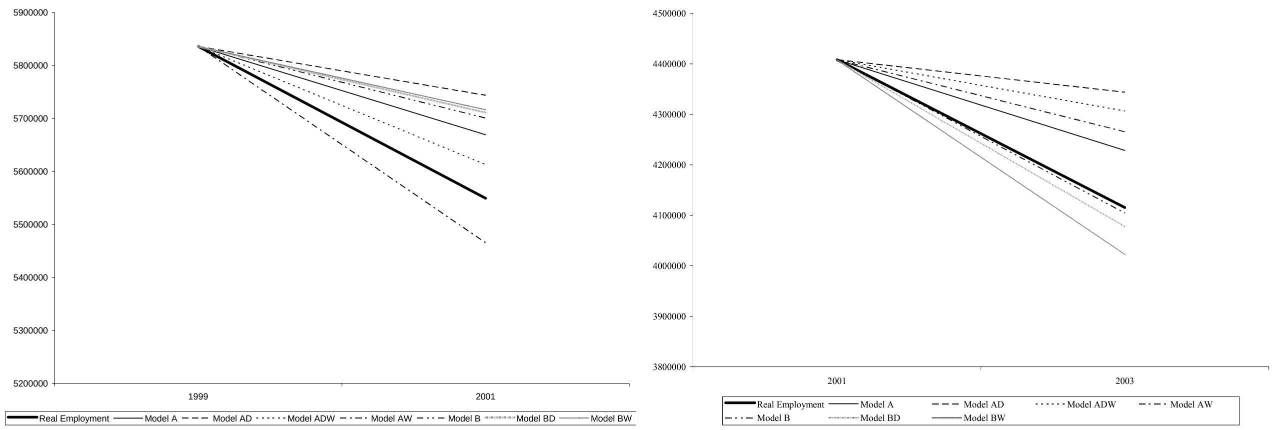


Figure 3 – Aggregate NN forecasts for the years 2001 (left) and 2003 (right); the case of East Germany

Concluding, the general result that we can obtain from the statistics presented in Table 3, as well as from the aggregate forecasts shown in Figure 3, is the following: as for the case of West Germany, the B-type models, based on time fixed effects, seem to mostly outperform the A-type models, based on time dummies.

3.4 Concluding Remarks: The Evaluation of Neural Network Models Results

The results presented in the last two subsections described the performance of NN models – in the years 2001 and 2003 – as tools for forecasting short-term employment variations in Germany. This is particularly true for B-type NN models, which are based on the use of a 'time fixed effect' variable. However, statistical results are not always consistent over different testing periods. Systematic evaluation tools are then necessary to assess the stability of the NN models. In this context, the 'measurement' and evaluation of the performance of the NN models, adopted under a wider set of criteria, constitute an additional, powerful methodological instrument.

The stability of the models' performance can be measured by analysing the persistence of their ranks, over time and different statistical indicators. In this context, Friedman's rank correlation statistic (Friedman 1937) was employed, by testing a subset of the models previously presented (see Patuelli et al. 2004). This analysis showed that different NN models tend to have a consistent rank under different statistical indicators, as well as over different forecasting years. Furthermore, the NN models separately developed for West and East Germany were shown to have correlated rankings. This result seems to support the previous findings concerning the tendency by the B-type models to win over the A-type models.

If the objective is to go beyond the simple assessment of stable rankings of the NN models, more sophisticated multi-objective evaluation tools can be employed, such as MCA (see, for example, Nijkamp and Voogd 1985). In this further context, an MCA of a set of NN models has also been carried out (Patuelli et al. 2003). This analysis showed that, when the evaluation of the models is uncertain because of conflicting values in the criteria employed, MCA can be a helpful tool in assessing the NN models' performance. MCA provides a ranking, which is based on priorities (weights) assigned to each statistical test (or, in general, criterion). The choice of the weights is, evidently, a critical passage in the application of such an analysis.

On the basis of the previous results, confirmed by an evaluation analysis, the last step of our forecasting procedure consisted in testing our NN models, by embedding a conventional solid tool, often adopted in regional economic analysis: the shift-share approach. This joint NN-shift share approach will be presented in the next section.

4. New Neural Network Experiments

4.1 Prologue

The preceding section presented the results obtained for NN models developed for employment forecasting in Germany, for the years 2001 and 2003. As new data become available, the models – and their respective forecasts – need re-testing, on the basis of the newly acquired data. The related results – concerning the years 2004, 2005 and 2006 – will be illustrated later in Sections 4.3 and 4.4. In the context of employment forecasts in these three recent years, new NN approaches will be proposed, in addition to the NNs previously adopted. In particular, these new NN models will incorporate shift-share analysis (SSA) components, as shown next in Section 4.2.

4.2 The Joint 'Neural Network–Shift-Share' Approach

In this section, we will show the results emerging from a new set of models, viz. NNs embedding shift-share (NN-SS) components. These new 'NN-SS' models will be tested *ex post*, by forecasting employment variation for the period 2002–04, as well as presenting forecasts for the 2003–05 and 2004–2006 periods.

SSA was developed, first by Dunn (1960) and, subsequently, by others (Fuschs 1962; Ashby 1964), as a tool for improving the understanding of changes in economic variables, such as employment or GDP, at the regional level. SSA is often employed in: a) forecasting; b) strategic planning; c) policy evaluation; and d) decision making (Dinc et al. 1998; Loveridge and Selting 1998). SSA consists of the decomposition of the growth observed in an economic variable. In our case, the employment growth observed in a given region and sector is split into three components:

- a national effect;
- a sectoral effect, given by the difference between the sectoral growth rate and overall national growth rate;

- a competitive effect, given by the difference between the local and nationwide sectoral growth rates.

This identity can be simply written as follows:

$$\Delta e_i = [G + (G_i - G) + (g_i - G_i)]e_i, \tag{2}$$

where Δe_i is the employment observed in a given region for sector i; G is the overall employment growth rate in the nation; G_i is the national growth rate of sector i; and g_i is the region's growth rate, again for sector i.

Three new NN-SS models are proposed in this section, which employ additional explanatory variables derived from SSA approaches. All NN models are based on the basic structure of Model B, which employs time fixed effects. The B-type structure was chosen because, as seen in Section 3, the B-type models seem to outperform the A-type models, using time dummies, for both West and East Germany. The models are defined as follows:

- Model BSS is based on the conventional, deterministic shift-share decomposition described in Equation (2). The 'competitive effect' component, $(g_i - G_i)$, computed for each of the nine sectors i and for all regions, is added, in Model BSS, to the basic structure of Model B, resulting in nine additional explanatory variables. Only the competitive effect is employed here, as it is the only SSA component that is region-specific.
- Model BSSN is based on a recent extension of SSA, developed by Nazara and Hewings (2004), and called 'spatial shift-share'. This SSA extension takes into account the spatial aspects of regional growth, such as spillover effects, and so on, which are not contemplated in classic SSA. In spatial shift-share, the national growth rate of sector i, G_i (see Equation 2), is substituted by the component $\vec{g}_i$. This is defined, for each region r, as the growth rate, in sector i, of region r's neighbours. The resulting shift-share identity is:

$$\Delta e_i = [G + (\vec{g}_i - G) + (g_i - \vec{g}_i)]e_i, \tag{3}$$

where $\vec{g}_i$ is computed as:

$$\widetilde{g}_i = \left(\sum_{S=1}^{r} \widetilde{w}_{rs} e_{is}^{t+1} - \sum_{S=1}^{r} \widetilde{w}_{rs} e_{is}^{t} \right) \Bigg/ \sum_{S=1}^{r} \widetilde{w}_{rs} e_{is}^{t}, \tag{4}$$

where $\widetilde{w}_{rs}$ is a component of the row-standardized weight matrix $\widetilde{\mathbf{W}}$, which defines the contiguity of region r with its neighbours. Neighbours are defined, here, as the three regions that provide the largest number of commuters to the region considered. As for Model BSS, we employ, in our experiments, the competitive component of the shift-share identity, that is, the difference between region r's employment growth and that of its neighbours.
- Model BSSR is based on regression techniques, equivalent to SSA, developed by, amongst others, Patterson (1991) and subsequently used, for example, by Blien and Wolf (2002). 'Shift-share regression' aims to overcome one limitation of classic SSA: the lack of hypothesis testing. Our approach is a simplification of that employed by Blien and Wolf. We tested, by means of Weighted Least Squares (WLS) regressions, a model using the competitive effect components

computed in deterministic SSA as regressors, and the overall district employment growth rates as a dependent variable. Statistical tests were carried out separately for each 2-year period. We found most of the competitive effect variables to be statistically significant (for details, see Tables A.1 and A.2 in Annex A). In order to implement these findings in Model BSSR, the competitive components employed in Model BSS were multiplied, for each year, for their corresponding regression coefficient. This process might be seen as a 'fine-tuning' of the variables introduced in Model BSS.

These NN-SS models previously illustrated will be employed for additional forecasts, carried out on current data. In the next sections, we will show the results of their performance. In particular, *ex post* forecasts for the year 2004 will be presented, as well as estimates of employment variations for the years 2005 and 2006.

4.3 *Ex post* Forecasts for the Year 2004

This section presents the NN results, as well as the NN-SS results, concerning the *ex post* forecasts carried out, for both West and East Germany, on the year 2004. This is the most recent year for which employment data are available. Testing our NN-SS models – together with the 'old' NN models – on a more recent year enables us to: a) examine once more the statistical performance of the previously-developed models; b) evaluate the new models; and, generally, c) assess how they fit the current labour market scenarios. Table 4 illustrates the results obtained for the West and East German models. For the sake of brevity, only the B-type models are shown in this table.

Table 4 – Statistical performance of the *ex post* forecasts for the years 2004

West Germany	*Model B*	*Model BD*	*Model BW*	*Model BSS*	*Model BSSN*	*Model BSSR*
MSE	2213570	2612326	3137475	2194846	2001280	4802468
MAE	850.39	923.52	992.63	842.78	800.14	1128.57
MAPE	1.8947	1.9818	2.1820	1.8677	1.7842	2.3349
Theil's U	0.1049	0.1238	0.1487	0.1040	0.0949	0.2277
East Germany	*Model B*	*Model BD*	*Model BW*	*Model BSS*	*Model BSSN*	*Model BSSR*
MSE	1081583	1632222	1702475	1171623	1218817	1067005
MAE	732.01	818.68	774.38	733.07	760.70	734.42
MAPE	2.6044	2.7859	2.6605	2.5831	2.6894	2.6312
Theil's U	0.0298	0.0450	0.0470	0.0323	0.0336	0.0294

It is again evident, from Table 4, that the NN models show, as also outlined in Section 3, a rather homogeneous performance. In addition, the models' forecasting error displays lower values than those measured for the previous years (2001 and 2003), for both the West and East Germany (for a comparison, see Tables 2 and 3). Table 4 indicates that no model wins over the others at all times. Model BSSN (incorporating spatial shift-share components) is the winning model for West Germany, while, for East Germany, the performance of the models is so homogeneous that three different winners are found, concerning three statistical indicators (MSE, MAE, and MAPE).

In general, these finding show that it is not the additional explanatory variables which determine the forecasting power of the models presented, but instead the use of 'time fixed effects'. At the aggregate level, the set of NN models tested in Table 4 displays corroborating results (Figure 4), as it approximates the actual observed employment variations by 0.7 and 0.5 per cent, for West and East Germany, respectively.

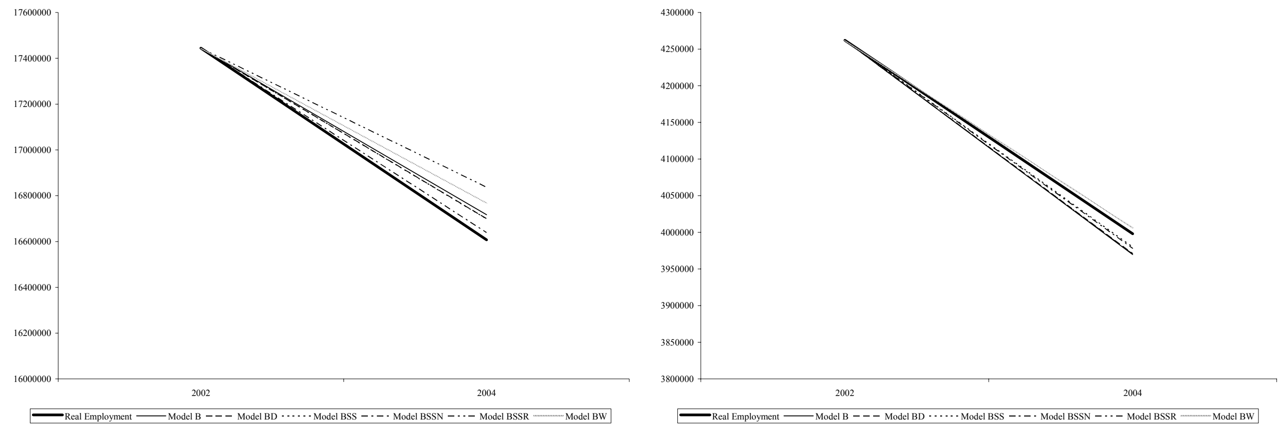
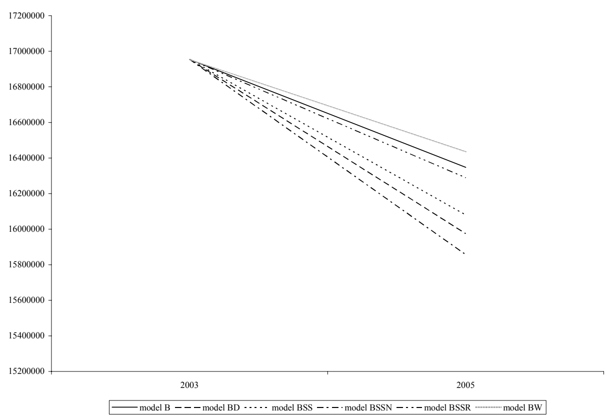


Figure 4 – Aggregate *ex post* forecasts of NN and NN-SS models for the year 2004: West Germany (left) and East Germany (right)

Once both newer and older NN models have been statistically evaluated, it is desirable to carry out actual forecasts, aside from the *ex post* estimates. The next section presents the forecasts made for the years 2005 and 2006, on the basis of the NN models presented above.

4.4 Forecasts for the Years 2005 and 2006

In order to carry out forecasts for the years 2005 and 2006, a double training process had to take place. Our NN and NN-SS models underwent two separate training phases: a) first, the models were trained utilizing data until the year 2003, and computing two-step-ahead forecasts, that is, for the year 2005; subsequently, b) the models were trained until 2004, in order to generate forecasts for the year 2006. Figure 5 shows the aggregate estimates of the NN models for the year 2005.

a)


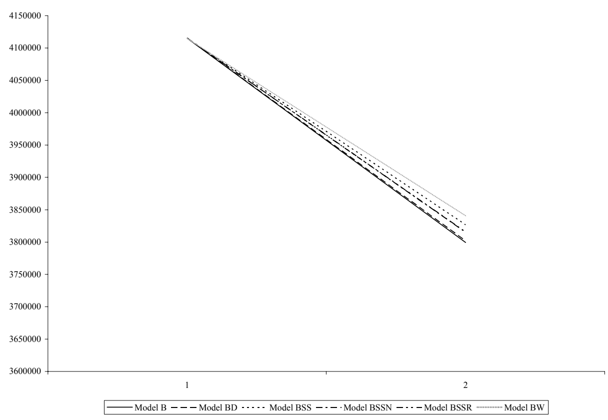
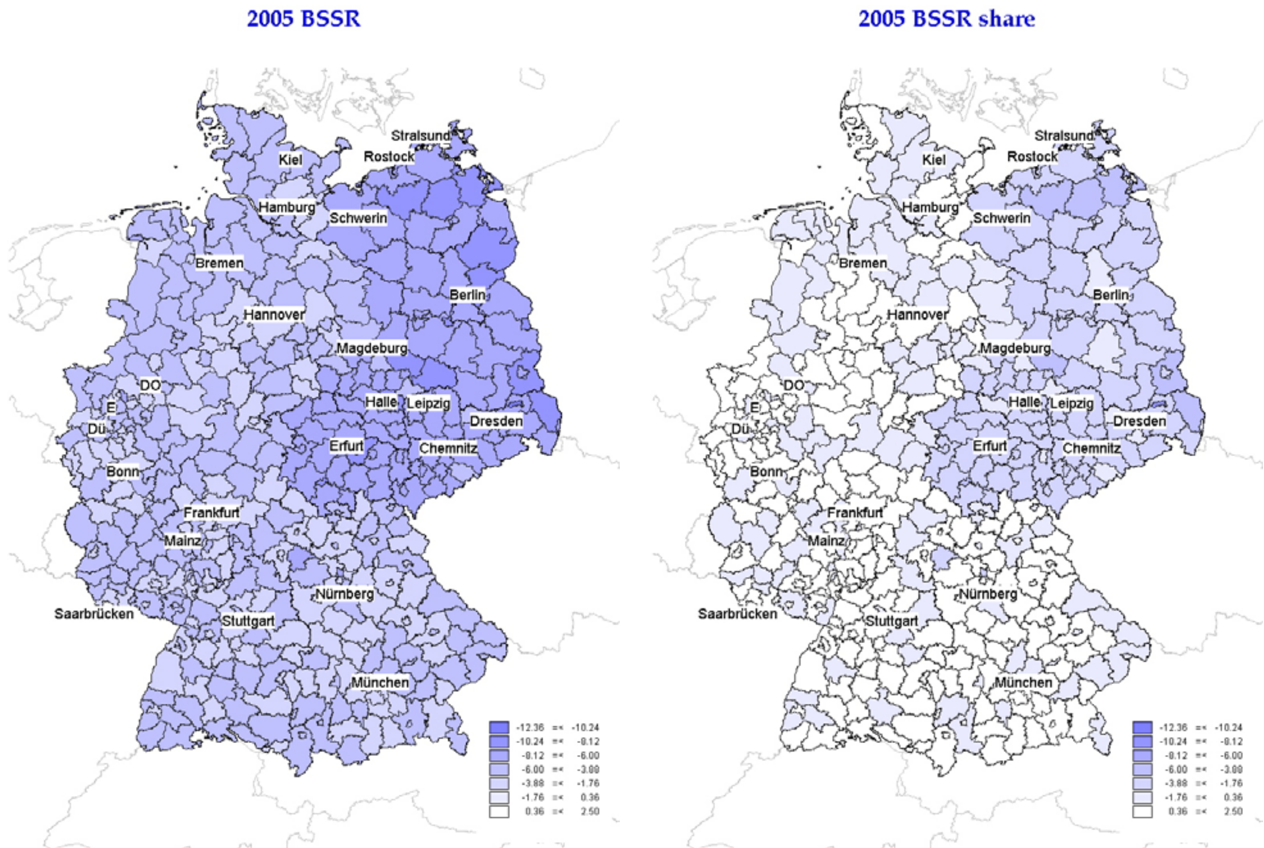
b)


Figure 5 - Aggregate NN forecasts for the year 2005: a) West Germany; and b) East Germany

Figure 5 offers a graphical illustration of the range of forecasts given by our NN and NN-SS models. First, in the case of East Germany, all the NN and NN-SS models seem to converge towards a unique value (Figure 5b), meaning an average decrease in full-time employment of 7.26 per cent. This might be due to the fact that East Germany shows a more homogeneous employment tendency (that is, a negative tendency). Opposite trends can instead be found in West Germany (for example, Bavaria's socio-economic wealth, in contrast to the difficult situation of areas closer to the former East/West boundaries), which can generate more heterogeneous forecasts. Second, all models agree in forecasting a further decline of full-employment in the West, as in the East. However, the decrease estimated for West Germany is smaller, averaging 4.66 per cent. Overall, the average expected decrease in Germany is 5.17 per cent (not shown here).

However, it should be noted that the aggregate trends in Figure 5 do not offer sufficient insight into the employment variations at the local scale. This regional aspect is specified in the percentage change of: a) the employees in each district (that is, the growth rate), and b) the district's regional share of employment (for details concerning this latter variable, see Bade 2006). Figure 6 shows two maps of the results obtained by Model BSSR.

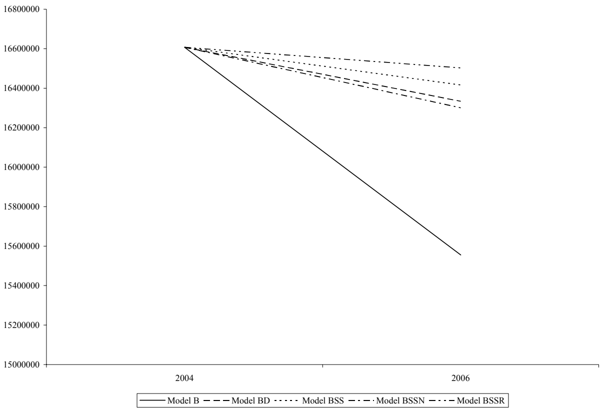


a) b)

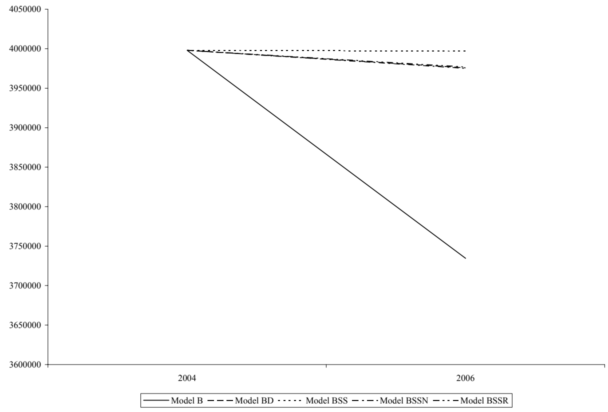
Figure 6 – Maps of German districts growth rate (a) and relative share change (b) forecasted for the 2003–05 period: Model BSSR

The left map shows the district growth rates, while the right map shows the change in the districts' regional employment share. In this context, we can observe a more marked decrease of employment in East Germany, already seen in Figure 5. As for West Germany, more heterogeneous and less negative results – though still negative – are estimated. In terms of regional share variation, the East German districts seem to further lose importance in the national employment totals.

As a final step in the presentation of the forecasts computed in this work, we present preliminary forecasts of full-time employment for the year 2006. Figure 7 provides a graphical visualization of the overall employment figures forecasted by the NN and NN-SS models. Model BW is not employed here, because of the unavailability of updated wage data. It is evident from Figure 7 that, while the forecasts for the year 2005 (Figure 6) were fairly homogeneous, the ones for 2006 are not – or at least not completely. Model B (full line in the graphs) shows, in fact, a rather negative forecast, for both West and East Germany, meaning –6.34 and –6.59 variations, respectively. This strong negative result for both West and East Germany is quite singular, since each model was developed separately for the two areas. On the contrary, the remaining models (Model BD and the three SSA-inspired NN models) show a less significant decline in employment. While the West German models – minus Model B – suggest an average 1.32 per cent decrease, the loss is 0.42 per cent in East Germany. As a consequence, the overall variation estimated for full-time employment in Germany is –6.39 per cent for Model B, and, on average, –1.14 per cent for the remaining models (not shown here). This is a much smaller decrease, if compared with the variation of about –5 per cent observed for the 2002–04 period. The slighter losses forecasted are a new element, in particular for East Germany, since the area's employment decline in the previous years has been fairly consistent around 6–7 per cent (bi-annually) since the 1999–2001 period.



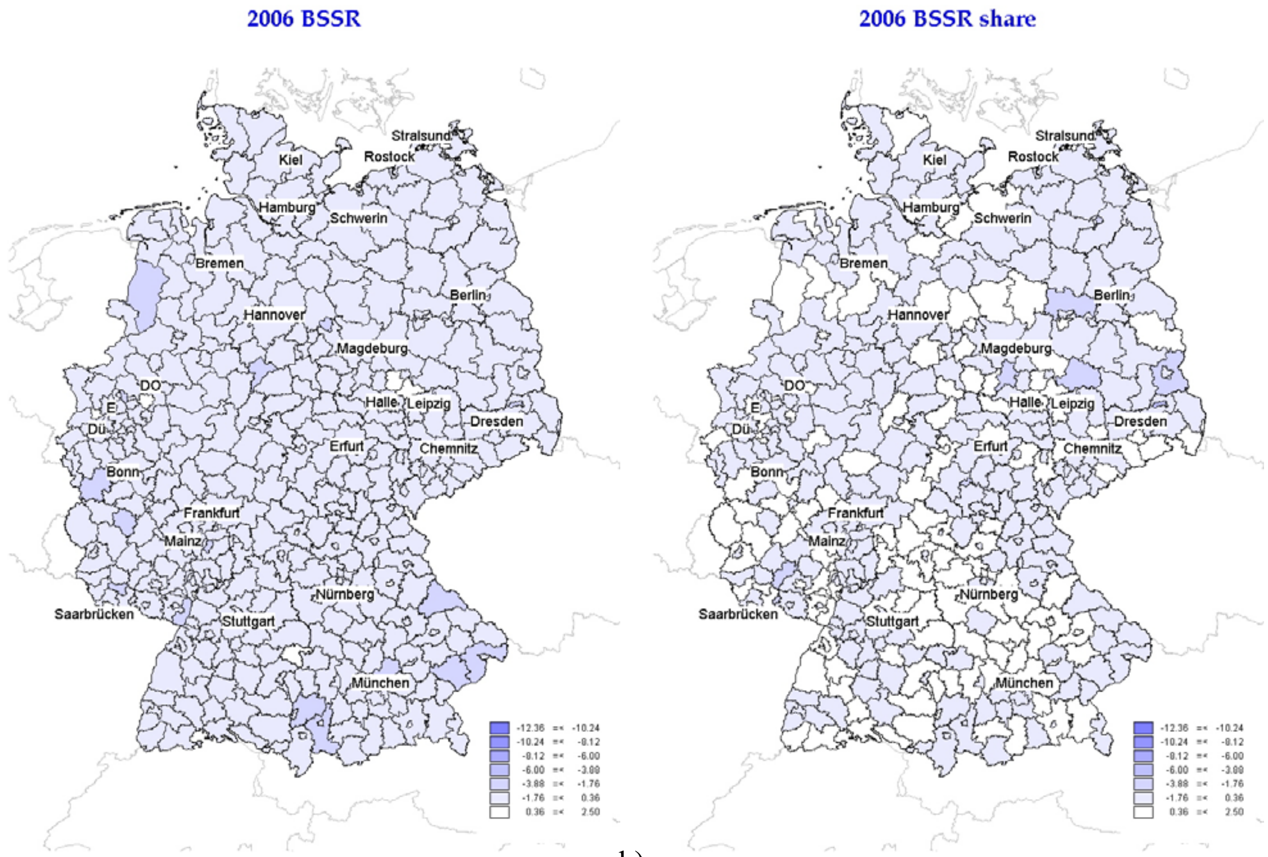
a)



b)

Figure 7 – Aggregate NN forecasts for the year 2006: a) West Germany; and b) East Germany

Having shown the aggregate 2006 forecasts, we now focus on the employment variation at the regional scale. Figure 8 shows the growth rate of the German districts, computed for the year 2006 (left map), as well as the change in their relative share (right map), according to Model BSSR.



a) b)

Figure 8 – Maps of German districts growth rate (a) and relative share change (b) forecasted for the 2004–06 period: Model BSSR

The graphical visualizations in Figure 8 are consistent with the aggregate results shown in Figure 7. Model BSSR seems to show a homogeneous pattern of employment variation, with almost indistinguishable differences between West and East Germany. No particular macro-area seems to have a significantly difference performance. This would be consistent with the findings from the previous years of analysis, as with the general economic trends observed in Germany over recent years.

5. Conclusions

This paper has reviewed NN experiments carried out in order to forecast full-time employment variations in Germany, at the regional level. Two data sets at the NUTS 3 aggregation level were employed for training NN models that aim at forecasting 2-years-ahead (t+2) employment in West and East Germany. Three types of NN models were developed: a) the A-type models, which employ time dummies; b) the B-type models, in which the time component is expressed in a 'fixed effects' fashion, similarly to traditional panel analysis techniques; and c) the B-type models employing different SSA components as explanatory variables (called 'NN-SS' models). The NN and NN-SS models' performance was subsequently evaluated by means of a set of statistical indicators.

Concerning the NN models mentioned in points a) and b) above, a review of the average statistical results for the years 2001 and 2003 was presented in Section 3. In this respect, the following considerations can be made:

a) Considerable differences in the statistical performance of the two families of NN models can be observed. The B-type models (time fixed effects) clearly outperform the A-type models (time dummies) on both the West and East German data.
b) Generally, the error levels of the NN models seem to be slightly lower for West Germany. This finding might be justified by the longer time span – six additional years – of the West German data. As said, the B-type models show, in both cases, lower errors.
c) The NN models' performance was also tested against a naïve no-change-hypothesis random walk model (see Theil's U statistic in Tables 2 and 3). Because of their lower MSE, the B-type models were found to largely outperform the random walk model.

The results concerning the experiments based on the NN-SS approach ((c) above) were illustrated in Section 4. On the basis of the good performance of the B-type models for the years 2001 and 2003, this typology of models were also employed for the additional 2004–06 experiments and compared with the SSA-inspired models. The emerging results showed that these NN-SS models seem to slightly improve the accuracy of the 2004 forecasts. A general decline of the error levels was also observed, as well as increased ability to outperform a no-change random walk model.

Concerning the aggregate patterns emerging from the forecasts, while the 2004 and 2005 forecasts suggested a further decline of full-time employment (with reference to the previous years), the 2006 forecasts highlighted a partial cycle inversion. Additional information is provided by investigating the results' visualization in terms of regional share change:

- In the year 2005, while minor changes can be observed in West Germany, the East German districts lose relative importance;
- in the year 2006, the changes in relative importance seem to be distributed rather evenly over Germany.

Concluding, our experiments showed the potential of NN models to effectively forecast regional employment variations. In particular, the NN models employing time fixed effects seem to generally reduce the error levels, as well as their variability. However, a prudent consideration is necessary here, since our experiments only employed two main variables (time and sectoral employment), which can not include all the factors that may come into play in determining socio-economic changes. A step in this direction is the use of the NN-SS models, which enable a mix of linear and non-linear methods to be introduced in the NN processing, and show better results.

Further research should move in several directions. In particular, from the methodological view point, it is worth investigating: i) new NN families as an alternative to feedforward NNs, such as recurrent or stochastic NNs, which would allow for different interaction among computational units; ii) a more thorough consideration of shift-share regression in our models, and its expansion, such as the development of a combined spatial shift-share and regression shift-share approach;[12] iii) the integration of NNs with spatial techniques, such as spatial filtering (see, for example, Griffith 2003), which would allow the use of spatial patterns as explanatory variables; and iv) the definition of dedicated NN evaluation indices for panel data processing, in order to assess, at the same time, the overall generalization properties of the models, as well as the accuracy of the single regional forecasts.

From the empirical viewpoint, the implementation of the NN refinements described above will undoubtedly be a necessary task. Furthermore, the investigation – by means of NNs – of the employment forecasts at the time (t+1) will be taken into account.

From the policy view point, the choice of the results – concerning (un)employment variations – in terms of either growth rate or relative share change will be a critical issue, as well as the robustness of results under varying future socio-economic and technological scenarios.

These research directions will be tested in future experiments.

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Annex A – Details of Shift-Share Regression Parameter Estimates

Tables A.1 and A.2 present the regression coefficients found when regressing the districts' overall growth rates on the competitive effect variable seen in Equation (2), for West and East Germany, respectively. A competitive effect variable was used for each of the nine industry sectors. Weighted least squares regressions were carried out for each year (that is, for each 2-year period). Carrying out separate year-by-year regressions seemed to be necessary in order to provide any additional information to the NNs. A unique model accounting for time would have computed a single set regression coefficients, resulting in only modifying the scale of the variables once the coefficients were applied to them.

Table A.1 – Shift-share regression parameters for the competitive effect variables: the case of West Germany

Sector	*87–89*	*88–90*	*89–91*	*90–92*	*91–93*	*92–94*	*93–95*	*94–96*	*95–97*	*96–98*	*97–99*	*98–00*	*99–01*	*00–02*	*01–03*	*02–04*
Primary sector	0.060***	0.109***	0.087***	0.051***	0.042***	0.061***	0.022***	0.012***	0.012*	0.015***	0.028***	0.028***	0.018***	0.021***	0.035***	0.031***
Industry goods	0.246***	0.195***	0.195***	0.269***	0.295***	0.244***	0.231***	0.211***	0.221***	0.197***	0.242***	0.256***	0.265***	0.195***	0.183***	0.242***
Consumer goods	0.038***	0.049***	0.053***	0.074***	0.085***	0.072***	0.058***	0.053***	0.032***	0.054***	0.053***	0.057***	0.038***	0.036***	0.044***	0.040***
Food manufacturing	0.030**	0.019	0.061***	0.033***	0.031***	–0.021	0.025***	0.024***	0.015**	0.018***	0.000	0.020*	0.017	0.001	0.015*	0.019**
Construction	0.044**	0.073***	0.039**	0.043**	0.038*	0.099***	0.096***	0.067***	0.046***	0.004	0.002	–0.022	–0.001	0.058***	0.062***	0.075***
Distributive services	0.156***	0.146***	0.109***	0.090***	0.135***	0.140***	0.107***	0.137***	0.115***	0.152***	0.167***	0.093***	0.197***	0.186***	0.158***	0.143***
Financial services	0.060***	0.075***	0.056***	0.066***	0.052***	0.033*	0.068***	0.099***	0.100***	0.105***	0.097***	0.075***	0.117***	0.112***	0.118***	0.078***
Household services	0.029***	0.058***	0.116***	0.057***	0.052***	0.042**	0.045***	0.043***	0.060***	0.084***	0.074***	0.090***	0.058***	0.077***	0.053***	0.052***
Services for society	0.161***	0.106***	0.139***	0.188***	0.080***	0.110***	0.127***	0.092***	0.164***	0.181***	0.093***	0.097***	0.155***	0.209***	0.201***	0.177***

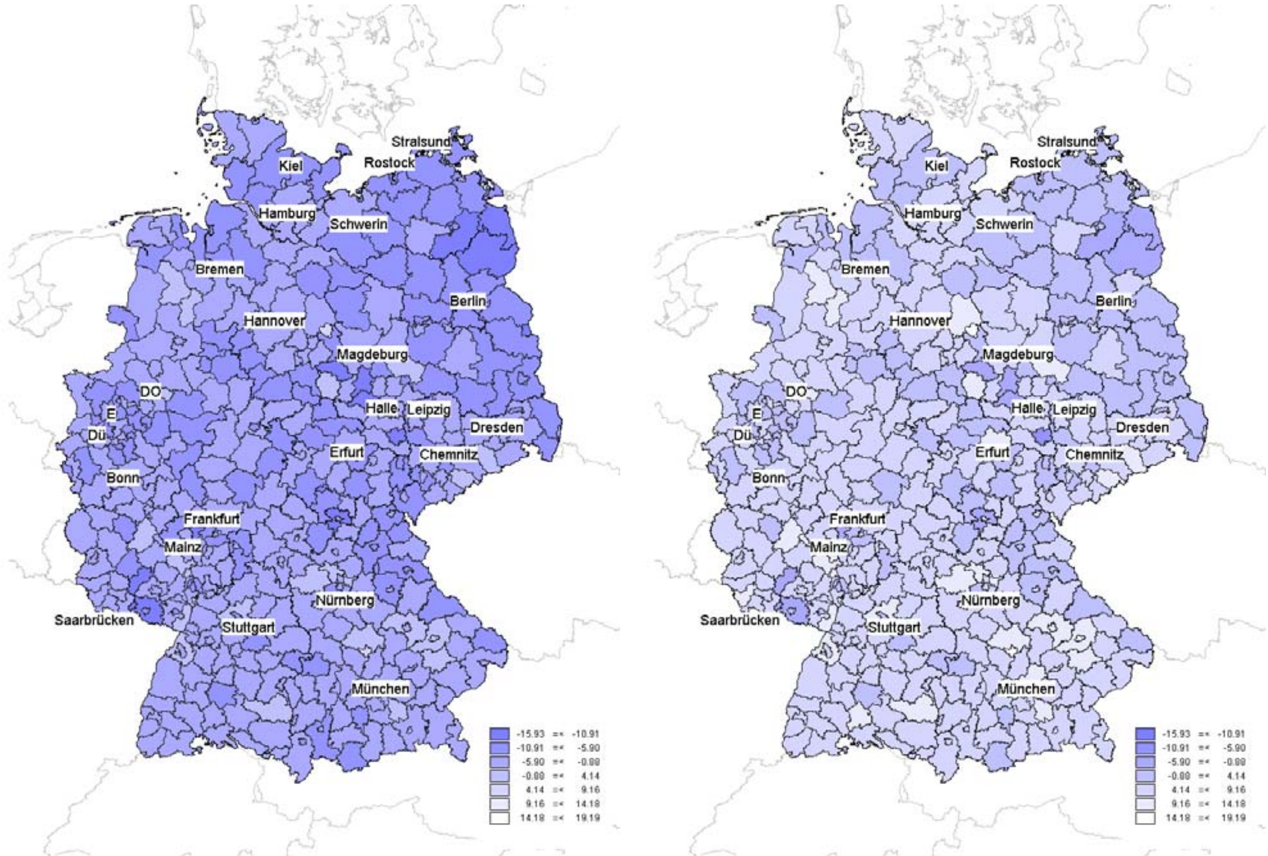
Notes:
*** Significant at the 99 per cent level.
** Significant at the 95 per cent level.
* Significant at the 90 per cent level.

Table A.2 – Shift-share regression parameters for the competitive effect variables: the case of East Germany

Sector	*93–95*	*94–96*	*95–97*	*96–98*	*97–99*	*98–00*	*99–01*	*00–02*	*01–03*	*02-04*
Primary sector	0.077***	0.097***	0.073***	0.056***	0.056***	0.054***	0.011	0.035***	0.040***	0.040***
Industry goods	0.150***	0.103***	0.096***	0.135***	0.135***	0.114***	0.157***	0.139***	0.104***	0.100***
Consumer goods	0.008	0.002	0.011	–0.011	–0.011	0.035**	0.040***	0.035**	0.026**	0.022**
Food manufacturing	0.035**	0.017	0.009	0.009	0.009	0.013	0.035***	0.015	–0.001	–0.007
Construction	0.151***	0.144***	0.187***	0.210***	0.210***	0.158***	0.172***	0.076***	0.102***	0.104***
Distributive services	0.181***	0.211***	0.123***	0.139***	0.139***	0.115***	0.191***	0.195***	0.141***	0.121***
Financial services	0.043***	0.089***	0.091***	0.101***	0.101***	0.126***	0.176***	0.166***	0.097***	0.105***
Household services	0.004	–0.027	0.055**	–0.002	–0.002	0.140***	0.098***	0.086***	0.031	0.058***
Services for society	0.208***	0.175***	0.306***	0.288***	0.288***	0.267***	0.302***	0.275***	0.252***	0.287***

Notes:
*** Significant at the 99 per cent level.
** Significant at the 95 per cent level.

Annex B – Map of Observed Growth Rates and Relative Share Change (Years 2002–04) in Germany



a) b)

Note: Relative share change is defined, for each district, as the ratio between the district's growth rate and the overall national growth rate.

Figure B.1 – Growth rate (a) and regional share change (b) of German districts for the 2002–04 period

Notes

[1] Neural networks were originally developed as optimization tools that could replicate the type of simultaneous information processing and learning seen in biological networks. Rosenblatt (1958) first introduced an artificial NN, while Werbos (1974) provided a mathematical framework for it. Rumelhart and McClelland (1986) later developed the backpropagation algorithm, a commonly used error-correction method.

[2] Additional details on NNs and their internal functioning can be found in Fischer (2001a; 2001b).

[3] An estimator of the generalization power of NNs was computed by the authors in Patuelli et al. (2003).

[4] NUTS stands for 'Nomenclature of Territorial Units for Statistics', which is a coding standard, developed by the European Union, for referencing geographically-referenced variables within countries. The reference number in NUTS 1, 2 or 3 refers to the level of (increasing) geographical disaggregation considered (see http://europa.eu.int/comm/eurostat/ /ramon/nuts/home_regions_en.html).

[5] The nine economic sectors are obtained by aggregating 12 industries, and result in the following classification: 1) primary sector; 2) industry goods; 3) consumer goods; 4) food manufacturing; 5) construction; 6) distributive services; 7) financial services; 8) household services; 9) services for society. It should be noted that, because of a change in the firms'

classification system, there is a percentage of employees who can not be allocated to a specific industry classification. These missing data amount to about 2 per cent of the total in 2003, and about 3–4 per cent in 2004. A definitive solution to this problem is currently in progress.

[6] The classification by the BBR (Bundesanstalt für Bauwesen und Raumordnung) (Böltgen and Irmen 1997) organizes both West and East German districts as follows: 1) central cities in regions with urban agglomerations; 2) highly-urbanized districts in regions with urban agglomerations; 3) urbanized districts in regions with urban agglomerations; 4) rural districts in regions with urban agglomerations; 5) central cities in regions with tendencies towards agglomeration; 6) highly-urbanized districts in regions with tendencies towards agglomeration; 7) rural districts in regions with tendencies towards agglomeration; 8) urbanized districts in regions with rural features; and 9) rural districts in regions with rural features.

[7] The commercial software used for carrying out our experiments, Neuralyst, enables non-numeric (string) input and output variables to be used. The software processes such variables by associating their values with numeric values between 0 and 1. The interpretation and mapping of the relationship between the numeric and non-numeric variables are automatically taken care of by a built-in algorithm.

[8] For each NN model, five structures were experimented with at the initial stage. First, a 2-layer structure was tested, followed by three 3-layer models, containing 5, 10 and 15 neurons, respectively, in one hidden layer. Finally, a 4-layer model was attempted, using 5 neurons for each of the hidden layers.

[9] The NN models presented in this paper are evaluated by means of the following statistical indicators:

- Mean Absolute Error: MAE = $1/N * [\Sigma_i |y_i - y_i^f|]$;
- Mean Square Error: MSE = $1/N * [\Sigma_i (y_i - y_i^f)^2]$;
- Mean Absolute Percentage Error: MAPE = $1/N * [\Sigma_i |y_i - y_i^f| * 100/y_i]$; and
- Theil's U: MSE (NN model)/MSE (random walk),

where y_i is the observed value (target); y_i^f is the forecast of the model adopted (NN); and N is the number of observations/examples. Theil's U statistic compares the performance of the NN models with the performance of a no-change-hypothesis random walk model, by computing the ratio between their MSE indicators (see Armstrong and Collopy 1992). The MAPE indicator and Theil's U were not used in the validation phase, but only in the evaluation of the *ex post* forecasts.

[10] Longhi (2005) suggests the use of a 'rolling' training data set, which would eliminate the first year of data employed, when data for a new year become available or are utilized. In our case, when switching from 2001 to 2003 *ex post* forecasts, the first two years of our data set would exit the NN training sample. This practice deserves future testing because of its clear computational advantages, and for the diminishing influence that early years have on economic variables as years go by.

[11] A sensitivity analysis would be desirable, which examines how the performance of the NNs varies once data for earlier years are excluded from the learning process phase. This aspect will be examined in future research.

[12] The recent decomposition by Nazara and Hewings (2004) is, in fact, already the subject of further study. For example, Fernández and López Menéndez (2005) have developed a mixed Nazara and Hewings/Esteban-Marquillas model, joining the use of homothetic employment and the spatial information given by a contiguity matrix. Recent applications of shift-share regression can also be found in Blien and Suedekum (2004) or Fritz and Streicher (2004).