Forecasting Regional Employment in Germany: A Review of Neural Network Approaches

Peter Nijkamp, Aura Reggiani, Roberto Patuelli

Objectives:

• To develop and apply Neural Network (NN) models in order to forecast regional employment growth in Germany
• To compare the statistical performance of the basic NN models
• To propose new NN models, as well as to update forecasts on more recent data
• To compare the NN results in terms of regional growth rate and relative change of employment share
Structure of the Paper

- Neural Network Models for Forecasting Employment in Germany
  - Neural Networks as a Flexible Optimization Tool
  - The Theory
- The Data
- Empirical Application of Neural Network Models to Labour Market in West and East Germany
  - Implementation of the Neural Networks Adopted
  - Results for West Germany: 2001 and 2003 ex post forecasts
  - Results for East Germany: 2001 and 2003 ex post forecasts
  - Evaluation of Neural Network Models Results
- New Results in Neural Network Forecasting
  - The Joint “Neural Network-Shift-Share Analysis” Approach
  - Ex post Forecasts for the Year 2004
  - Forecasts for the Years 2005 and 2006
- Conclusions
Neural Network Models for Forecasting Employment in Germany: The Approach

• Artificial Neural Networks (NNs) are optimization algorithms based on:
  • Distribution of the computational activity on a high number of calculation units (the neurons), connected by weights and working in parallel
  • Ability to learn the functional relationships between the variables from the data
  • No modelling hypotheses necessary
Neural Network Models for Forecasting Employment in Germany: The Theory

- The generic units $u_i$ (represented by circles) are defined as a function of the previous calculation units and a set of weights $w$.
- An activation function computes the unit’s output.
Neural Network Models for Forecasting Employment in Germany: The Adopted Methodology

Evaluation of proposed NN models

• Comparison with widely-accepted conventional econometric models. Forecasts from the NN models should be at least as accurate as those generated by a naïve extrapolation, such as random walk
• Test of the models’ out-of-sample performance for comparing different methodologies
• Use of a appropriate sample size (from the numerosity view point)
The Data

Data available:

- Information about the total number of **persons fully employed** every year on June 30th
- The total number of employees is subdivided in **nine** economic sectors, from primary sector to services for society
- Average regional daily wages earned by full-time workers
- Type of economic region (different urbanization levels) (slide 7)

- Panel of 439 districts (326 for the former West Germany and 113 for the former East Germany) available for:
  - 18 years (1987 to 2004) for the former West Germany
  - 12 years (1993 to 2004) for the former East Germany
# Type of Economic Region (Details)

<table>
<thead>
<tr>
<th>Group</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Regions with urban agglomeration</td>
<td>1. Central cities</td>
</tr>
<tr>
<td></td>
<td>2. Highly urbanized districts</td>
</tr>
<tr>
<td></td>
<td>3. Urbanized district</td>
</tr>
<tr>
<td></td>
<td>4. Rural districts</td>
</tr>
<tr>
<td>B. Regions with tendencies towards agglomeration</td>
<td>5. Central cities</td>
</tr>
<tr>
<td></td>
<td>6. Highly urbanized districts</td>
</tr>
<tr>
<td></td>
<td>7. Rural districts</td>
</tr>
<tr>
<td>C. Regions with rural features</td>
<td>8. Urbanized districts</td>
</tr>
<tr>
<td></td>
<td>9. Rural districts</td>
</tr>
</tbody>
</table>
Trends in Full-Time Employment Data

Aggregate trends for Germany

West Germany (left) 1987-2004

East Germany (right) 1993-2004
First Empirical Applications of Neural Network Models to Labour Market in West and East Germany

Outline

- *Ex post* NN forecasts of full-time employment for the years:
  - 2001
  - 2003

- Evaluation of regional results by means of statistical indicators (MSE, MAE, MAPE, Theil’s U) (slide 12)

- Visualization of aggregate results
Implementation of the Neural Networks Adopted

- We developed **seven** NN models, by using, as input variables, the lagged \((t - 2)\) growth rate of sectoral employment and time.
  - Other variables: type of district and/or wages.
  - The output variable is **district employment growth rate**

- **Training:**
  - NN models for the f. East Germany: years 1997-1999

- **Validation (choice of NN structure):**
  - NN models for the f. West Germany: years 1999-2000
  - NN models for the f. East Germany: year 2000

- **Testing:**
  - (Re-training until the year 2000) Year 2001
  - (Re-training until the year 2002) Year 2003
## Implementation of the Neural Networks Adopted (2)

<table>
<thead>
<tr>
<th>Model</th>
<th>Input Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model A</td>
<td>Growth rate of sectoral employment; time <em>dummies</em></td>
</tr>
<tr>
<td>Model AD</td>
<td>Growth rate of sectoral employment; time <em>dummies</em>; type of economic region fixed effects</td>
</tr>
<tr>
<td>Model DW</td>
<td>Growth rate of sectoral employment; time <em>dummies</em>; type of economic region fixed effects; growth rate of daily wages</td>
</tr>
<tr>
<td>Model AW</td>
<td>Growth rate of sectoral employment; growth rate of daily wages; time <em>dummies</em></td>
</tr>
<tr>
<td>Model B</td>
<td>Growth rate of sectoral employment; time <em>fixed effects</em></td>
</tr>
<tr>
<td>Model BD</td>
<td>Growth rate of sectoral employment; time <em>fixed effects</em>; type of economic region fixed effects</td>
</tr>
<tr>
<td>Model BW</td>
<td>Growth rate of sectoral employment; growth rate of daily wages; time <em>fixed effects</em></td>
</tr>
</tbody>
</table>
Evaluation of the NN Models’ Performance

- We evaluated the performance of the NN models by means of four statistical indicators:
  - Mean Squared Error:
    - \[ \text{MSE} = \frac{1}{N} \sum_i (y_i - y_i^f)^2 \]
  - Mean Absolute Error:
    - \[ \text{MAE} = \frac{1}{N} \sum_i |y_i - y_i^f| \]
  - Mean Absolute Percentage Error:
    - \[ \text{MAPE} = \frac{1}{N} \sum_i \frac{|y_i - y_i^f|}{y_i} \times 100 \]
  - Theil’s U statistic:
    - \[ \text{MSE (NN model)}/\text{MSE (random walk)} \]
Results for West Germany: 2001 and 2003 ex post Forecasts

Average statistical performance for 2001 and 2003

- The B-type models seem to outperform the A-type models
- The NN models outperform a naive no-change-hypothesis random walk model (see Theil’s U)
Aggregate results for West Germany:

2001 (left)

2003 (right)

In 2003, only the B-type models estimate the right trend (negative)
Results for East Germany: 2001 and 2003 ex post Forecasts

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Model A</th>
<th>Model AD</th>
<th>Model ADW</th>
<th>Model AW</th>
<th>Model B</th>
<th>Model BD</th>
<th>Model BW</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>11735072</td>
<td>22200869</td>
<td>21108442</td>
<td>32489364</td>
<td>5760466</td>
<td>5504239</td>
<td>6816745</td>
</tr>
<tr>
<td>MAE</td>
<td>1534.36</td>
<td>2147.65</td>
<td>1712.01</td>
<td>1598.35</td>
<td>1312.86</td>
<td>1370.54</td>
<td>1502.80</td>
</tr>
<tr>
<td>MAPE</td>
<td>3.9248</td>
<td>5.5472</td>
<td>4.1054</td>
<td>3.3474</td>
<td>3.6260</td>
<td>3.8070</td>
<td>4.0034</td>
</tr>
<tr>
<td>Theil's U</td>
<td>0.8892</td>
<td>0.9954</td>
<td>1.2933</td>
<td>2.9720</td>
<td>0.5940</td>
<td>0.5501</td>
<td>0.5177</td>
</tr>
</tbody>
</table>

Average statistical performance for 2001 and 2003

- The B-type models seem to outperform the A-type models
- Model AW is competitive only when error is computed as percentage (MAPE)
- The NN models again outperform the no-change-hypothesis random walk model
Aggregate results for East Germany:

2001 (left) 2003 (right)
Evaluation of Neural Network Models Results

- The **B-type models** seem to be winning, for 2001 and 2003, over the A-type models for both West and East Germany.

- The stability of the models’ performance can be measured by analysing their **ranks**, over time and different statistical indicators:
  - Analyses by means of **Friedman’s rank correlation statistic** (Patuelli et al. 2004). The NN models tend to have a consistent rank under different statistical indicators, as well as over different forecasting years.
  - **Multi-objective** evaluation tools can be employed, such as **MCA**:
    - MCA of a set of NN models (Patuelli et al. 2003). MCA can be a helpful tool in assessing the NN models’ performance.
Recent Results in Neural Network Forecasting: Years 2004-06

- **New models proposed:**
  - The Joint “Neural Network-Shift-Share Analysis” Approach

- **New forecasts on the basis of more recent data:**
  - Ex post forecasts for the year 2004
  - Forecasts for the years:
    - 2005
    - 2006

- **Only B-type models considered, given the previous results**
The Joint ‘Neural Network-Shift-Share Analysis’ Approach

• Shift-share analysis (SSA):
  • A tool for improving the understanding of changes in economic variables at the regional level.
  Dunn (1960); Esteban-Marquillas (1972); Nazara and Hewings (2004)

Classical formulation:

\[\Delta e_i = [G + (G_i - G) + (g_i - G_i)]e_i\]

- National effect \((G)\)
- Sectoral effect \((G_i - G)\)
- Competitive effect \((g_i - G_i)\)

• Shift-share regression (Patterson 1991)

• Joint approach: NNs embedding shift-share components
The Joint ‘Neural Network-Shift-Share Analysis’ Approach (2)

- Model BSS: based on the conventional, deterministic SSA. The ‘competitive effect’ component, \((g_i - G_i)\), computed for each of the nine sectors \(i\) and for all regions, is added, to Model B.

- Model BSSN: based on Nazara and Hewings’ extension (2004) (‘spatial shift-share’). Takes into account the spatial aspects of regional growth. The national growth rate of sector \(i\), \(G\), is substituted by the component

\[
\Delta e_i = \left[ G + (\tilde{g}_i - G) + (g_i - \tilde{g}_i) \right] e_i,
\]

defined, for each region \(r\), as the growth rate, in sector \(i\), of region \(r\)’s neighbours. Neighbours are defined as the three regions that provide the larger number of commuters to the region considered.

- Model BSSR: based on regression techniques equivalent to SSA. Overcomes SSA’s lack of hypothesis testing. Simplification of Blien and Wolf’s approach:
  - Regressors: Competitive effect components computed in deterministic SSA
  - Dependent variable: Overall district employment growth rates
  - Statistical tests were carried out separately for each 2-year period
  - The competitive components were multiplied, for each year, for their corresponding regression coefficient → ‘fine-tuning’ of the variables introduced in Model BSS

- In all cases, only the competitive effect components are employed in the NN models, because region-specific
**Ex post** Forecasts of NN and NN-SS Models for the Year 2004

<table>
<thead>
<tr>
<th></th>
<th><strong>NN Models</strong></th>
<th><strong>NN-SS Models</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>West Germany</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Model</strong> B</td>
<td>2213570</td>
<td>1081583</td>
</tr>
<tr>
<td><strong>Model</strong> BD</td>
<td>2612326</td>
<td>1632222</td>
</tr>
<tr>
<td><strong>Model</strong> BW</td>
<td>3137475</td>
<td>1702475</td>
</tr>
<tr>
<td><strong>Model</strong> BSS</td>
<td>2194846</td>
<td>1171623</td>
</tr>
<tr>
<td><strong>Model</strong> BSSN</td>
<td>2001280</td>
<td>1218817</td>
</tr>
<tr>
<td><strong>Model</strong> BSSR</td>
<td>4802468</td>
<td><strong>1067005</strong></td>
</tr>
</tbody>
</table>

**MSE**

- West Germany: 2213570, 2612326, 3137475, 2194846, 2001280, 4802468
- East Germany: 1081583, 1632222, 1702475, 1171623, 1218817, **1067005**

**MAE**

- West Germany: 850.39, 923.52, 992.63, 842.78, 800.14, 1128.57
- East Germany: 732.01, 818.68, 774.38, 733.07, 760.70, 734.42

**MAPE**

- West Germany: 1.8947, 1.9818, 2.1820, 1.8677, 1.7842, 2.3349
- East Germany: 2.6044, 2.7859, 2.6605, **2.5831**, 2.6894, 2.6312

**Theil's U**

- West Germany: 0.1049, 0.1238, 0.1487, 0.1040, **0.0949**, 0.2277
- East Germany: 0.0298, 0.0450, 0.0470, 0.0323, 0.0336, **0.0294**

- All models show a rather homogeneous performance
- No model wins over the others at all times
- The NN-SS models seem to perform slightly better than older models
Aggregate West and East German Results (2004)

Aggregate results West and East Germany:

West Germany (left)  East Germany (right)
Forecasts for the Year 2005 (growth rate): Model B and Model BSSR
Forecasts for the Year 2005 (relative share change): Model B and Model BSSR
Aggregate West and East German Forecasts (2005)

Aggregate results West and East Germany:

West Germany (left)  East Germany (right)
Forecasts for the Year 2006 (growth rate): Model B and Model BSSR
Forecasts for the Year 2006 (relative share change): Model B and Model BSSR
Aggregate results West and East Germany:

West Germany (left)  East Germany (right)

Model B gives a pessimistic forecast for both West and East Germany
Conclusions

• This presentation reviewed NN experiments carried out in order to forecast full-time employment variations in Germany, at the regional level.

YEARS 2001 AND 2003
• Two types of NN models developed:
  • A-type: based on time dummies
  • B-type: based on time fixed effects
• The B-type models clearly outperform the A-type models, for 2001 and 2003, West and East Germany
• B-type NN models outperform a naïve no-change-hypothesis random walk

YEARS 2004-06
• NN models embedding shift-share seem to slightly improve Model B’s forecasting power (ex post forecasts for 2004)
• Comparison of results in terms of growth rate and relative share change
• Forecasts for the year 2005 show homogeneously negative trends
• Forecasts for the year 2006 (minus Model B) suggest less negative trends, and hence a possible cycle inversion, in particular for East Germany
Future Research Directions

THEORETICAL AND METHODOLOGICAL VIEW POINT

• Exploration of NN families alternative to feedforward NNs, such as recurrent or stochastic NNs
• A more thorough implementation of shift-share regression in the NN models
• A combined spatial and regression shift-share approach
• Integration of NNs and other spatial techniques, such as spatial filtering (Griffith, 2000) – use of spatial patterns as explanatory variables
• Definition of dedicated NN evaluation indices for panel data forecasting, in order to assess:
  • The overall generalization properties of the models
  • The accuracy of the single regional forecasts
Future Research Directions (2)

EMPIRICAL VIEW POINT

- Investigation – by means of the above NNs – of employment forecasts at time (t+1)
- Study of unemployment forecasts at both times (t+1) and (t+2)

POLICY VIEW POINT

- Choice/Use of results – concerning (un)employment variations – in terms of either growth rate or relative share change will be a critical issue
- Robustness of results under varying future socio-economic and technological scenarios
Thank You for your attention

Questions and comments are welcomed