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Dynamic Panel Data Approach to the Forecasting of the GDP of German Länder

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Dynamic Panel Data Approach to the Forecasting of the GDP of German Länder

Berlin, February 2007
Opinions expressed in this paper are those of the author and do not necessarily reflect views of the institute.
Dynamic panel data approach to the forecasting of the GDP of German Länder

Konstantin A. Kholodilin*  Boriss Silverstovs**  Stefan Kooths§

February 9, 2007

Abstract

In this paper we forecast the annual growth rates of the real GDP for each of the 16 German Länder (States) simultaneously. To the best of our knowledge, this is the first attempt in the literature that addresses this question for all German Länder as most of the studies try to forecast the German GDP either on the aggregate level or focus on selected Länder only. Our further contribution to the literature is that next to the usual panel data models such as pooled and within models we apply within models that explicitly account for the spatially autocorrelated errors. On the one hand, it allows us to take advantage of the panel dimension, given the short sample for which the data are available, and hence gain efficiency and precision. On the other hand, accounting for the spatial heterogeneity and correlation is important due to the substantial differences existing between the German regions, in particular between East and West Germany. Our main finding is that pooling helps to significantly (up to 25% in terms of the root mean squared forecast errors) increase the forecasting accuracy compared to the individual autoregressive models estimated for each of the Länder separately.

Keywords: German Länder; forecasting; dynamic panel model; spatial autocorrelation.

JEL classification: C21; C23; C53.

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*We are very grateful to J. P. Elhorst for having provided his Matlab code and for having patiently explained necessary details.

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## Contents

1. Introduction  
2. Data properties  
3. Dynamic panel data models  
4. Estimation results  
5. Forecasting performance  
6. Summary  
References  
Appendix
List of Tables

1. Descriptive statistics of the growth rates of real GDP of the German Länder (%) ........................................... 10
2. Estimation results 1991 - 2005 .................................................................................................................. 11
3. Testing for spatial autocorrelation of the original time series and of the model residuals, all Länder 1993-2005 ................................................................. 12
4. Forecasting performance, all Länder 2002-2005 ..................................................................................... 13

List of Figures

1. Fiscal and investment indicators in Eastern Länder (% of Western level), 1991-1997 ........................................ 14
1 Introduction

In this paper we forecast the annual growth rates of the GDP for each of the 16 German Länder (singular Land). To the best of our knowledge, this is the first attempt in the literature that addresses this question for all German Länder simultaneously as most of the studies try to forecast the German GDP on the aggregate level. These studies include Langmantel (1999), Hinze (2003), Dreger and Schumacher (2004), Mittnik and Zadrozny (2004), Kholodilin and Siliverstovs (2005), and Schumacher (2005), among others, who use several variants of the forecasting methodology of Stock and Watson (2002) based on diffusion indices in order to predict the developments in the German GDP. At the same time, there are two studies that construct forecasts for the individual German Länder such as Bandholz and Funke (2003) and Dreger and Kholodilin (2006) who forecast the GDP of Hamburg and of Berlin, respectively, again, using the diffusion indices.

The fact that GDP data for individual German Länder are not available on a quarterly basis severely reduces the post-re-unification data base to 16 annual observations for the period from 1991 to 2005. This may explain the small number of studies aiming at forecasting the German GDP on the Länder level. This scarcity sharply contrasts with the importance of regional economic analysis and forecasting for a federal country like Germany. In addition, there exists the East-West distinction, which is rooted in the post-World War II history, when Germany was split into two states: one with a market economy and another with a centrally planned economy. While the Eastern Länder showed a distinct boom pattern in the first five years after re-unification (which was mainly attributable to expansionary fiscal policy for fostering the transformation of the Eastern economy), the catching-up process came to a premature end when the expansionary fiscal impulses stopped. Therefore, even 16 years after re-unification, the Eastern German economy is still significantly different from its Western counterpart. Besides this West-East difference, there is also substantial heterogeneity within each group. This implies that regional forecasts might diverge from the forecasts made for the whole country, which hence cannot serve as a meaningful guide for decision-making at the regional level.

In this paper, we circumvent the problem of data collection for each regional entity by pooling the annual growth rates of the GDP into a panel and correspondingly utilizing panel data models for forecasting. The advantages of such a pooling approach for forecasting have been widely demonstrated in a series of articles for diverse data sets such as Baltagi and Griffin (1997); Baltagi et al. (2003) — for gasoline demand, Baltagi et al. (2000) — for cigarette demand, Baltagi et al. (2002) — for electricity and natural gas consumption, Baltagi et al. (2004) — for Tobin’s q estimation, and Brücker and Siliverstovs (2006) — for international migration, among others.

Thus, the main contribution of the paper is the construction of GDP forecasts for all German Länder simultaneously. Our additional contribution to the literature is that for this purpose we employ panel data models that allow not only for temporal interdependence in the regional growth rates, but also take into account their spatial interdependence. While there is a rather
large number of studies that demonstrate the superiority of the pooling approach in forecasting by imposing the homogeneous temporal structure on each cross-sectional unit, there is still a limited number of studies that illustrate the usefulness of accounting for (possible) spatial dependence effects across the cross-sections in the forecasting exercise. For example, Longhi and Nijkamp (2006); Patuelli et al. (2006) and Baltagi and Li (2004) where the forecasts of the German regional labor markets and the demand for liquor in the states of the USA were computed by using panel data models that account for the spatial interdependence across the regions, respectively.

The paper is structured in the following way. In section 2 the data are described. Section 3 presents different econometric forecasting models. In section 4 the estimation results are reported, whereas section 5 evaluates the forecasting performance of the alternative models. Finally, section 6 concludes.

2 Data properties

For the estimation and forecasting we use annual real GDP data of the 16 German Länder. The data cover the period 1991-2005 and can be downloaded from the webpage of the Statistical Office of the Länder Baden-Württemberg (Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder). The data are working-days adjusted and expressed in constant prices with the base year 2000.

Before we estimate the models described in Section 3, we take a look at the descriptive statistics of the data under consideration displayed in Table 1. In this table, the basic descriptive statistics of the growth rates of real GDP in form of the mean, maximum, minimum, and the standard deviation are summarized at three levels of aggregation: for all German Länder, separately for the Western Länder group and for the Eastern Länder group as well as for each Land individually.

The specific economic dynamics of the Eastern Länder in the first half of the 1990s reflects the re-unification growth effect that was mainly driven by expansionary government interventions (see Vesper (1998) and Bach and Vesper (2000) for a detailed analysis of fiscal policies during this period). Some illustrative indicators are shown in Figures 1 and 2. The market-oriented transformation of the formerly centrally planned economy in Eastern Germany and the rebuilding of the infrastructure in the Eastern Länder implied public per capita spending that was far above the Western level from the start and rising until the mid-1990s (from 128% in 1992 to 145% in 1995). This expansionary government program was fuelled by both extensive transfers from West to East (starting at 65 billion DM in 1991 and peaking at 118 billion DM in 1996) and deficit spending in the Eastern Länder whose per capita debt quickly approached the Western levels (within the first 5 years this ratio rose from 11% to 90%). Furthermore, due to tax privileges (like special depreciation allowances) the construction sector boomed in the first decade with the East-West ratio of per capita investment more than doubled from 67% in 1991 to 180% in 1996 (residential construction more than tripled in the same period). As can be seen from Figures 1 and 2, the special factors that heavily influenced the catching-up process lost momentum after 1995 (no further increase, but stagnation or even decrease of the indicators). Therefore, we have chosen to split the whole period 1992-2005 into two sub-periods: from 1992 till 1995 and from 1996 till 2005.
Figure 3 shows the median growth rates for the Eastern and Western Länder. In the first sub-period the growth rates of the Eastern Länder were much higher than those of the Western Länder. Nevertheless, after 1995 this difference has vanished such that in the second sub-period the real GDP growth rates in both groups became very similar.

The more precise figures on the magnitude of the difference in the growth rates in the Eastern and Western Länder for the period from 1992 till 1995 can be found in Table 1. In this period, in all Eastern Länder, except Berlin, the mean growth rates of real GDP was about 10% per annum, such that the average growth rate computed for all Eastern Länder is 8.7 which is about 17 times higher than the average growth rate of 0.5 reported for the Western Länder in this sub-period. Furthermore, from 1992 till 1995 there were no negative growth rates in either of the Eastern Länder, whereas the Western Länder experienced the negative growth rates of real GDP during this sub-period.

In the second sub-period (from 1996 till 2005), the growth rates of real GDP become more or less similar in both the Eastern and Western Länder. The mean growth rates are of about the same magnitude (0.9 for the Eastern Länder vs 1.4 for the Western Länder) with virtually the same standard deviation of 1.4 vs 1.6, respectively.

This marked difference between the magnitude of the real GDP growth rates in the Eastern and the Western Länder in the first sub-period and the fact that it vanished in the second sub-period prompts us to introduce a step dummy variable in our regression models that takes the value of one in the period from 1992 up to and including 1995 and the value of zero otherwise. Observe that this step dummy is applicable only for the six Eastern Länder as namely for those Länder the properties of the real GDP growth rates are drastically different in the both sub-periods. As far as the properties of the real GDP growth rates in the Western Länder are concerned we assume that those did not change over the whole period.

We have chosen to interact this step dummy with the autoregressive coefficient in our regression models in order to account for the fact that the persistence in the growth rates of real GDP in the Eastern Länder in the first period seems to be much more pronounced than in the second sub-periods.

3 Dynamic panel data models

In this section we describe the econometric models that we are using for forecasting the growth rates of real GDP of the German Länder. In these otherwise standard models we include the re-unification boom dummy that takes into account specific macroeconomic dynamics of the Eastern Länder in the first half of the 1990s.

As a benchmark model, with which all other models will be compared, we are going to use a linear AR(1) model denoted here as individual autoregressive model and estimated for each Länder separately:

\[ y_{it} = \alpha_i + \alpha_{i1} y_{it-1} + \gamma_i I_{it} y_{it-1} + \epsilon_{it} \quad \epsilon_{it} \sim N.I.D.(0, \sigma_i^2) \]  

where \( I_{it} \) is a step re-unification boom dummy, which is defined as follows:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Eastern Länder</td>
<td>( I_{it} = 1 )</td>
<td>( I_{it} = 0 )</td>
</tr>
<tr>
<td>Western Länder</td>
<td>( I_{it} = 0 )</td>
<td>( I_{it} = 0 )</td>
</tr>
</tbody>
</table>
However, a rather small sample size makes this estimate very inefficient and subject to substantial changes when extending the sample by one observation. Therefore a good idea would be to get advantage of dynamic panel data (DPD) models.

The simplest panel model we are going to use here is the pooled model:

\[ y_{it} = \alpha_0 + \alpha_1 y_{it-1} + \gamma I_{it} y_{it-1} + \epsilon_{it} \quad \epsilon_{it} \sim N.I.D.(0, \sigma^2) \]  

(2)

This implies that both the intercept and slope coefficients are the same across all the Länder.

An alternative model is the within model that allows for region-specific intercepts and thus represents an intermediate case between the individual AR models and the pooled model:

\[ y_{it} = \alpha_{i0} + \alpha_1 y_{it-1} + \gamma I_{it} y_{it-1} + \epsilon_{it} \epsilon_{it} \sim N.I.D.(0, \sigma^2) \]  

(3)

Finally, it would also make sense to take into account the spatial autocorrelation that might exist between the Länder. One may expect to find the dynamic (stagnating) Länder being the neighbors of dynamic (stagnating) Länder due to cross-border spillovers (commuter labor and trade flows). This assumption can be translated into the dynamic panel model with spatially correlated errors (SAE), considered in Ellhorst (2005), and denoted here as within + spatial errors model:

\[ y_{it} = \alpha_{i0} + \alpha_1 y_{it-1} + \gamma I_{it} y_{it-1} + u_{it} \quad u_{it} = \lambda W u_{it} + \epsilon_{it} \quad \epsilon_{it} \sim N.I.D.(0, \sigma^2) \]  

(4)

where \( \lambda \) is the coefficient of spatial autoregression and \( W \) is the matrix of spatial weights.

Here we use two types of the spatial weights matrix \( W \): one based on the common borders between the Länder and another based on the distances between the Länder capitals.

The within model with SAE using the former specification of the weights matrix is denoted here as within + spatial errors model with weights based on the common borders. The typical element of the matrix \( W \) is equal to 1 if two corresponding Länder have a common border and 0, otherwise. All the elements on the main diagonal of matrix \( W \) are equal to zero.

The within model with SAE using the latter specification of the weights matrix is denoted here as within + spatial errors model with weights based on the distances. In this case, a typical element of the spatial weights matrix \( w_{ij} \) is defined as follows:

\[ w_{ij} = \begin{cases} 
0, & \text{if } i = j \\
\frac{1}{\sigma_{ij}^2}, & \text{if } d_{ij} \leq d \\
0, & \text{if } d_{ij} > d 
\end{cases} \]  

(5)

where \( d \) is a distance cutoff value. Here, as in Baumont et al. (2002) we consider four different cutoff values: first quartile, median, second quartile, and maximum distance. These values are computed across all the pairwise distances between the capitals of the German regions. The constructed weights matrices are then normalized such that all the elements in each row sum up to one.

4 Estimation results

The estimates of the temporal and spatial autoregressive coefficients of all the models are presented in Table 2. At first, we report the summary of the estimates of the temporal autoregressive coefficient \( \hat{\alpha}_1 \) obtained for a model estimated for each Land separately. The results of
Discussion Paper 664
K. A. Kholodilin et al.

4 Estimation results

this exercise reveal quite large heterogeneity in the obtained values. For all 16 Länder considered, the minimum value of the autoregressive coefficient estimate is $-0.129$ and the maximum is 0.330, while the median value is 0.074.

We also report the summary of the estimates of the step-dummy coefficient $\hat{\gamma}$ computed in the regression for each Eastern Länder. The magnitude of the corresponding estimate lies in the interval from 0.285 to 1.064 with a median value of 0.650. Such values of the estimate coefficient supports our observation, made earlier in Section 2, that the persistence in the real GDP growth rates in the Eastern Länder was much larger during the period from 1992 till 1995 than that during the period from 1996 till 2005.

Note that the individual autoregressive regressions seem to provide rather poor fit to the data as the values of the adjusted $R^2$ often turn negative. The corresponding median is $-0.045$. This is most likely due to the rather small sample period used in the estimation as well as the rather low persistence in the real GDP growth rates for the majority of observations.

The next two columns of Table 2 contain the estimation results obtained from the pooled model (2) and from the within model (3). For the pooled model, the estimated value of the autoregressive coefficient is 0.172 which is significant at the 5% level, whereas for the within model the corresponding value is 0.065 with a p-value of 0.125.

The value of the step-dummy coefficient $\hat{\gamma}$ is 0.552 and 0.637 for the pooled and the within models, respectively. It is significant even at the 1% level in either case. Thus, our estimation results concord with those obtained from the individual autoregressions that the persistence in the growth rates of real GDP in the Eastern Länder was much higher during 1992-1995 than during 1996-2005.

Finally, the last five columns of Table 2 contain the parameter estimates of the within model with spatial effects which we model with various weight matrices. Introducing spatial effects in our models is warranted by the high Moran’s I statistic which was measured for the growth rates of real GDP (see the first column of Table 3). For seven years out of 13 we reject the null hypothesis that the spatial effects are absent at the 1% level, for two years — at the 5% level, for one year — at the 10% level, and for the remaining three years the Moran’s I statistic is insignificant. Overall, we interpret these results as rather convincing evidence in favor of the presence of spatial correlation in our data.

Indeed, our estimation results confirm the presence of spatial autocorrelation in the growth rates of real GDP. The estimated spatial autocorrelation coefficient $\hat{\lambda}$ takes a rather high positive value of 0.600 for the within model with the spatial matrix based on common borders and of about 0.5 for the within models with the spatial matrices based on distances between the capitals of the Länder. These estimates of the spatial autocorrelation coefficient $\lambda$ are significant at the 1% level.

The success of our within models, which allow for spatial autocorrelation, is also evident from the last column of Table 3, where the estimated residuals are tested for remaining spatial autocorrelation. As seen, the estimated Moran’s I statistic is insignificant for most years. The mean value computed over all years is $-0.074$, which is much lower than the corresponding mean value of 0.531 obtained for the original series of the growth rates.

Moreover, the estimation results of the within model with the spatial autocorrelation also

\[1\text{In order to save space we report only the Moran’s statistic for the residuals of the within model with spatially correlated errors and weights matrix based on the common borders, since the residuals of the other three models with spatially autocorrelated errors display basically the same pattern.}\]
favorably compare with those of the models that do not take into account the possible spatial
dependence in economic dynamics between the Länder. In Table 3 the test results for spatial
autocorrelation in the residuals of the autoregressive models, the pooled model, and the within
model are also summarized. These models largely fail to remove the spatial dependence in
the data as in most cases the reported Moran’s I is significant at the conventional levels. The
corresponding mean value of the Moran’s I statistic computed for all years is 0.394, 0.392, and
0.412 for each of these models, which is much higher than that reported for the within model,
which explicitly models the spatial autocorrelation pattern (-0.074).

Another consequence of introducing the spatial autocorrelation in the within model is a
further drop in the value of the autoregressive coefficient which in those models takes a value
that is very close to zero. The corresponding parameter estimates of the temporal autoregression
are not significantly different from zero. At the same time, the estimated coefficient for the
step dummy \( \hat{\gamma} \) takes a value of about 0.67 and is highly significant.

To summarize, on the basis of our estimation results we conclude the following. First, the
growth rates of real GDP of the German Länder exhibit rather low temporal dependence except
for the period from 1992 till 1995 when the Eastern Länder enjoyed really high growth rates.
Our step dummy introduced to capture this effect turns out to be positive and highly significant
in all models that we considered in this paper. Second, the growth rates of real GDP exhibit
high spatial dependence, which we successfully modelled with the within model that allows for
spatial effects. Next, it remains to check whether, in the forecasting exercise, allowance for this
feature of the data will result in improved forecasts of the regional GDP.

5 Forecasting performance

The one-step ahead forecasts were made for all 16 Länder over the forecasting period 2002-2005.
The results are reported in Table 4. The forecasting performance is measured by the root mean
square forecast error (RMSFE) for each year from 2002 through 2005 and overall for all regions
and forecasting periods (denoted as total RMSFE). The individual autoregressive model serves
as a benchmark, to which the forecasting performance of all other models is compared. Hence,
the relative total RMSFE measures gains in forecasting accuracy from pooling.

The results of our forecasting exercise further strengthens the evidence previously reported
in a number of studies such as Baltagi and Griffin (1997); Baltagi et al. (2003), Baltagi et al.
(2000), Baltagi et al. (2002), Baltagi et al. (2004), and Brücker and Siliverstovs (2006), etc.
that pooling helps to improve forecast accuracy. As seen, the pooled OLS model produces
the RMSFE that is more than 20% less than that reported for the individual AR(1) models.
By allowing for the presence of the fixed effects we are able to achieve further improvement
in the forecast accuracy. The within models not accounting and accounting for the spatial
correlation effects produce a total RMSFE value that is about 25% less than that reported
for the benchmark model. In this respect, notice that the reported forecast accuracy gains in
terms of the total RMSFE of the panel data models are derived from the fact that for every
year (except for 2004 for the pooled OLS model) for which we have produced the forecasts the
the corresponding RMSFE of the panel data models is less than that reported for the benchmark
models.

Finally, when we compare accuracy of the forecasts reported for the within models without
and with spatial dependence matrix we find the latter models produce very marginal improvements in terms of the RMSFE. For example, the difference in the RMSFE for the within model with the spatial weights matrix based on common borders and for the usual within model is about one per cent. Thus, despite the fact that we have found statistically significant positive spatial autocorrelation in the growth rates of real GDP in the German Länder we tend to conclude that accounting for the spatial dependence contributes very little if anything to the forecast accuracy when compared to the within model where such spatial effects are not modelled. Thus, our conclusion conforms with that reached in Baltagi and Li (2004) about at best marginal improvement in the forecast accuracy of the models that model the spatial autocorrelation explicitly.

We have also conducted the modified Diebold-Mariano test for equal forecast accuracy produced by the benchmark AR(1) model and by the panel data models, see Diebold and Mariano (1995) and Harvey et al. (1997), as well as the modified forecast encompassing test of Harvey et al. (1998). According to the results of the Diebold-Mariano test the null hypothesis of equal forecast accuracy of the benchmark and the pooled OLS model can only be rejected at the 15% significance level. The corresponding p-value is 0.123. The null hypothesis of equal forecast accuracy of the benchmark individual AR(1) model and either panel data model based on the within transformation (with or without accounting for spatial autocorrelation in the residuals) can be rejected at the 10% significance level. Thus, the difference in forecast accuracy brought about by pooling the data is statistically significant.

A more convincing evidence in favor of pooling comes from the results of the forecast encompassing test. As seen, the null hypothesis that the benchmark individual AR(1) model encompasses the forecasts of the competing models is rejected at the 5% significance level. At the same time, the null hypothesis that either of the competing panel data models encompasses the forecasts from the benchmark model cannot be rejected at the conventional significance levels.

6 Summary

In this paper we have addressed the forecasting of the growth rates of the real GDP of each of the 16 German Länder using panel data models. As suggested by various indicators we split the Eastern Länder’s data period in order to allow for special factors during the reunification boom in the first half of the 1990 decade.

Our main finding is that pooling helps to increase the forecasting accuracy which is consistent with the results obtained in Baltagi and Griffin (1997); Baltagi et al. (2003), Baltagi et al. (2000), Baltagi et al. (2002), Baltagi et al. (2004), and Brückner and Siliverstovs (2006), inter alia, for diverse data sets. For our data, we have observed that the forecasts from the pooled OLS, the within, and the within model with the spatial autocorrelation significantly improve the forecast accuracy in terms of the Root Mean Squared Forecast Errors, calculated for the period of 2002-2005. The outcome of the Diebold-Mariano testing procedure on whether forecast accuracy of the benchmark individual AR(1) model on the one hand and of the panel data models on the other hand is equal support the fact that the observed difference in the reported RMSFE is statistically significant. Moreover, the outcome of the forecast encompassing test indicates that the forecasts of the benchmark model are encompassed by the panel data models,
whereas the opposite is not true, i.e. we can reject the null hypothesis that the benchmark model forecast encompasses the panel data models.

We also note that, despite the fact that we were able to detect the presence of the spatial autocorrelation in our data, allowing for it in model parameter estimation does not generally result in higher forecasting accuracy over that provided by the within model without spatial effects.

References


References


## Table 1: Descriptive statistics of the growth rates of real GDP of the German Länder (%)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Mean</td>
</tr>
<tr>
<td>Total all</td>
<td>-4.4</td>
<td>3.6</td>
</tr>
<tr>
<td>West Länder</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baden-Württemberg</td>
<td>-4.3</td>
<td>0.2</td>
</tr>
<tr>
<td>Bayern</td>
<td>-1.8</td>
<td>1.0</td>
</tr>
<tr>
<td>Bremen</td>
<td>-2.9</td>
<td>-0.3</td>
</tr>
<tr>
<td>Hamburg</td>
<td>0.4</td>
<td>0.9</td>
</tr>
<tr>
<td>Hessen</td>
<td>-1.8</td>
<td>0.6</td>
</tr>
<tr>
<td>Niedersachsen</td>
<td>-1.0</td>
<td>0.6</td>
</tr>
<tr>
<td>Nordrhein-Westfalen</td>
<td>-2.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Rheinland-Pfalz</td>
<td>-2.9</td>
<td>0.2</td>
</tr>
<tr>
<td>Saarland</td>
<td>-4.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Schleswig-Holstein</td>
<td>-1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Total West</td>
<td>-4.4</td>
<td>0.5</td>
</tr>
<tr>
<td>East Länder</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Berlin</td>
<td>1.1</td>
<td>2.2</td>
</tr>
<tr>
<td>Brandenburg</td>
<td>7.3</td>
<td>9.8</td>
</tr>
<tr>
<td>Mecklenburg-Vorpommern</td>
<td>7.5</td>
<td>9.8</td>
</tr>
<tr>
<td>Sachsen-Anhalt</td>
<td>7.5</td>
<td>10.2</td>
</tr>
<tr>
<td>Sachsen</td>
<td>4.3</td>
<td>9.1</td>
</tr>
<tr>
<td>Thüringen</td>
<td>3.3</td>
<td>11.1</td>
</tr>
<tr>
<td>Total East</td>
<td>1.1</td>
<td>8.7</td>
</tr>
</tbody>
</table>
Table 2: Estimation results 1991 - 2005

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Individual</th>
<th>Pooled</th>
<th>Within</th>
<th>Within + spatial AR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Mean</td>
<td>Max</td>
<td>Cutoff: 1st quartile</td>
</tr>
<tr>
<td>$\hat{\alpha}_1$</td>
<td>-0.129</td>
<td>0.074</td>
<td>0.330</td>
<td>0.172**</td>
</tr>
<tr>
<td>$\hat{\gamma}$</td>
<td>0.285</td>
<td>0.650**</td>
<td>1.064**</td>
<td>0.552***</td>
</tr>
<tr>
<td>$\hat{\lambda}$</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>$R^2_{adj}$</td>
<td>-0.089</td>
<td>-0.045</td>
<td>0.820</td>
<td>0.589</td>
</tr>
</tbody>
</table>

$\hat{\alpha}_1$ – denotes the estimate of the temporal autoregressive parameter.
$\hat{\gamma}$ – denotes the estimate of the spatial autoregressive parameter.
$\hat{\lambda}$ – denotes the coefficient estimate of the unification-boom dummy.

***, **, * – denotes significance at 1%, 5%, and 10% levels.
### Table 3: Testing for spatial autocorrelation of the original time series and of the model residuals, all Länder 1993-2005

<table>
<thead>
<tr>
<th>Year</th>
<th>Original series</th>
<th>Individual AR(1)</th>
<th>Pooled</th>
<th>Within</th>
<th>Within + spatial AR and weights matrix based on common borders</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Moran's I</td>
<td>p-value</td>
<td>Moran's I</td>
<td>p-value</td>
<td>Moran's I</td>
</tr>
<tr>
<td>1993</td>
<td>0.555</td>
<td>0.015</td>
<td>0.570</td>
<td>0.012</td>
<td>0.530</td>
</tr>
<tr>
<td>1994</td>
<td>0.690</td>
<td>0.002</td>
<td>0.480</td>
<td>0.039</td>
<td>0.574</td>
</tr>
<tr>
<td>1995</td>
<td>0.657</td>
<td>0.003</td>
<td>0.505</td>
<td>0.029</td>
<td>0.469</td>
</tr>
<tr>
<td>1996</td>
<td>0.528</td>
<td>0.021</td>
<td>0.280</td>
<td>0.288</td>
<td>0.501</td>
</tr>
<tr>
<td>1997</td>
<td>0.676</td>
<td>0.002</td>
<td>0.317</td>
<td>0.211</td>
<td>0.293</td>
</tr>
<tr>
<td>1998</td>
<td>0.725</td>
<td>0.001</td>
<td>0.174</td>
<td>0.592</td>
<td>0.125</td>
</tr>
<tr>
<td>1999</td>
<td>0.833</td>
<td>0.000</td>
<td>0.675</td>
<td>0.002</td>
<td>0.475</td>
</tr>
<tr>
<td>2000</td>
<td>0.790</td>
<td>0.000</td>
<td>0.615</td>
<td>0.006</td>
<td>0.545</td>
</tr>
<tr>
<td>2001</td>
<td>0.128</td>
<td>0.761</td>
<td>-0.125</td>
<td>0.338</td>
<td>-0.005</td>
</tr>
<tr>
<td>2002</td>
<td>0.085</td>
<td>0.926</td>
<td>0.516</td>
<td>0.025</td>
<td>0.415</td>
</tr>
<tr>
<td>2003</td>
<td>-0.009</td>
<td>0.708</td>
<td>0.245</td>
<td>0.373</td>
<td>0.171</td>
</tr>
<tr>
<td>2004</td>
<td>0.799</td>
<td>0.000</td>
<td>0.593</td>
<td>0.009</td>
<td>0.532</td>
</tr>
<tr>
<td>2005</td>
<td>0.448</td>
<td>0.057</td>
<td>0.276</td>
<td>0.296</td>
<td>0.476</td>
</tr>
</tbody>
</table>

Mean Moran’s I: 0.531 0.394 0.392 0.412 -0.074

Residuals of the individual AR(1), Pooled, and Within models are defined as $\hat{u}_t = y_t - \hat{y}_t$, where $\hat{y}_t$ is the linear prediction of the dependent variable, while the residuals of the last model are calculated as $\hat{e}_t = (I - \lambda W)\hat{u}_t$. 
Table 4: Forecasting performance, all Länder 2002-2005

<table>
<thead>
<tr>
<th>Year</th>
<th>Individual</th>
<th>Pooled</th>
<th>Within</th>
<th>Within + spatial AR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Weights matrix based on</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Common Distance between capitals</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Cutoff:</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1st quartile</td>
</tr>
<tr>
<td>2002</td>
<td>0.0262</td>
<td>0.0180</td>
<td>0.0166</td>
<td>0.0164</td>
</tr>
<tr>
<td>2003</td>
<td>0.0194</td>
<td>0.0170</td>
<td>0.0170</td>
<td>0.0171</td>
</tr>
<tr>
<td>2004</td>
<td>0.0104</td>
<td>0.0115</td>
<td>0.0087</td>
<td>0.0082</td>
</tr>
<tr>
<td>2005</td>
<td>0.0118</td>
<td>0.0093</td>
<td>0.0098</td>
<td>0.0095</td>
</tr>
<tr>
<td>Total RMSFE</td>
<td>0.0181</td>
<td>0.0144</td>
<td>0.0136</td>
<td>0.0134</td>
</tr>
<tr>
<td>Relative RMSFE</td>
<td>1</td>
<td>0.796</td>
<td>0.750</td>
<td>0.741</td>
</tr>
<tr>
<td>DM</td>
<td>–</td>
<td>0.123</td>
<td>0.064</td>
<td>0.060</td>
</tr>
<tr>
<td>ENC₀</td>
<td>–</td>
<td>0.043</td>
<td>0.041</td>
<td>0.039</td>
</tr>
<tr>
<td>ENC₁</td>
<td>–</td>
<td>0.851</td>
<td>0.984</td>
<td>0.985</td>
</tr>
</tbody>
</table>

The table entries are the root mean squared forecast errors (RMSFE) computed for all the Länder for each year separately as well as for all years together (Total RMSFE).

DM — denotes the p-values of the modified Diebold-Mariano test statistic. The null hypothesis that the benchmark AR(1) model produces the forecast accuracy equal to that of a corresponding panel data model.

ENC₀ — denotes the p-values of the modified forecast encompassing test statistic. The corresponding null hypothesis is that the forecasts from the benchmark AR(1) model encompass the forecasts of a corresponding panel data model.

ENC₁ — denotes the p-values of the modified forecast encompassing test statistic. The corresponding null hypothesis is that the forecasts from a corresponding panel data model encompass the forecasts of the benchmark AR(1) model.
Figure 1: Fiscal and investment indicators in Eastern Länder (% of Western level), 1991-1997

Source: Statistisches Bundesamt, Bundesministerium der Finanzen, and own calculations
Figure 2: Public financial transfers and investment in Eastern Länder, 1991-1997

(a) Public financial transfers to Eastern Länder

(b) Growth rate of public financial transfers to Eastern Länder

(c) Public investment (Eastern Länder)

(d) Growth rate of public investment (Eastern Länder)

Source: Statistisches Bundesamt, Bundesministerium der Finanzen, and own calculations
Figure 3: Median growth rates of the real GDP: Eastern vs. Western Länder, 1992-2005