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Contents

Abstract

It is broadly accepted that two aspects regarding the modeling strategy are essential for the accuracy of forecast: a parsimonious model focusing on the important structures, and the quality of prospective information. Here, we establish a Global VAR framework, a technique that considers a variety of spatio-temporal dynamics in a multivariate setting, that allows for spatially heterogeneous slope coefficients, and that is nevertheless feasible for data without extremely long time dimension. Second, we use this framework to analyse the prospective information regarding the economy due to spatial co-development of regional labour markets in Germany. The predictive content of the spatially interdependent variables is compared with the information content of various leading indicators which describe the general economic situation, the tightness of labour markets and environmental impacts like weather. The forecasting accuracy of these indicators is investigated for German regional labour-market data in simulated forecasts at different horizons and for several periods.

Germany turns out to have no economically dominant region (which reflects the polycentric structure of the country). The regions do not follow a joint stable long run trend which could be used to implement cointegration. Accounting for spatial dependence improves the forecast accuracy compared to a model without spatial linkages while using the same leading indicator. Amongst the tested leading indicators, only few produce more accurate forecasts when included in a GVAR model, than the GVAR without indicator.

Zusammenfassung

Zwei Aspekte bezüglich der Modellierungsstrategie werden gemeinhin als entscheidend für die Genauigkeit von Prognosen betrachtet: Einerseits ein in den zu schätzenden Parametern sparsames Modell, welches nur die wichtigsten Zusammenhänge abdeckt; andererseits die Aussagekraft der vorausschauenden Information. Hier wird ein Mehrregionenmodell ähnlich einem Globalen Vektorautoregressiven (GVAR) Ansatz entwickelt. Diese Technik berücksichtigt verschiedene Strukturen der räumlich-zeitlichen Dynamik in multivariaten Gleichungssystemen, sie erlaubt regional heterogene Parameter und ist dennoch auch für Daten ohne sehr langen Beobachtungszeitraum geeignet. In diesem Modellrahmen werden regionale Co-Entwicklungen hinsichtlich ihrer vorausschauenden Information untersucht. Der Prognosegehalt räumlicher Abhängigkeiten wird dem Informationsgehalt von vorauseilenden Indikatoren gegenübergestellt, welche die allgemeine wirtschaftliche Lage, die Knappheit im Arbeitsmarkt und Umwelteinflüsse (wie etwa das Wetter) beschreiben. Die Prognosegenauigkeit wird mit deutschen regionalen Arbeitsmarktdaten in simulierten Prognosen auf unterschiedlichen Horizonten untersucht.
Die Existenz einer alle anderen bestimmenden Region wird für Deutschland abgelehnt (was die polyzentrische Struktur des Landes widerspiegelt). Die Regionen folgen keinem stabilen gemeinsamen Trend, der zur Implementierung einer Kointegrationsbeziehung genutzt werden könnte. Die Berücksichtigung regionaler Abhängigkeiten verbessert die Prognosegenauigkeit gegenüber einem Modell ohne diese, wenn derselbe vorausschauende Indikator verwendet wird. Nur wenige der geprüften Indikatoren tragen bei Berücksichtigung in einem GVAR zu einer genaueren Prognose im Vergleich zu einem GVAR ohne Indikator bei.

JEL classification: C 23; E 24; E 27; R 12

Keywords: Cross-sectional dependence; Global VAR; Labour market forecasting; Leading indicators; Regional forecasting; Spatio-temporal dynamics

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1 Introduction

Making predictions on the aggregate development of quantities and prices in the markets – e.g. GDP, inflation, liquidity demand, or as in this paper, unemployment and employment growth – is one of the most important tasks of the economic profession. Much of the recent criticism the discipline still has to face is due to the fact that neither the credit-crunch crisis (2008/2009) nor the Euro-zone crisis (2010 till present) were foreseen by a notable fraction of economists. Moreover, many of the GDP and labour-market forecast revisions made throughout the crisis turned out to be wrong as well, regardless of the statistical or economical model behind the forecasts.[1] Alike most parts of the Western hemisphere, the German economy suffered a strong decline in real GDP within one year[2] – but, in contrast to many countries, did not show a strong reaction in unemployment, a phenomenon denoted as the *German job miracle* (Möller, 2010). A weakening of the relation between GDP and unemployment is even observed in other countries, albeit at most as a jobless recovery. For example, the Chairwoman of the US 'Board of Economic Advisors' Christina Romer has remarked in the New York Times on Feb. 11, 2011:[3] "The usual relationship between GDP growth and the unemployment rate has broken down somewhat"; that is, labour market's dependence on expected production and the business cycle – stated by Okun's Law – may have relaxed. This encourages us to re-think the economic relations and indicators we previously employed for forecasting labour markets at the regional (and even at the national) level.

It is broadly accepted that two aspects regarding the modeling strategy are essential for the accuracy of forecasts: on the one hand a parsimonious model focussing on the important dependency structures and simplifying or omitting the less relevant, on the other hand the utilization of prospective information with a high information content. This paper deals with both issues in the context of forecasting regional labour markets; thus, its contribution to the literature is twofold. First, we establish a framework that considers spatiotemporal dynamics within the labour market in a multivariate setting. The model deals with the dimensionality problem of large heterogeneous spatial systems. It has the advantage of, in principle, allowing for both weak (spatially declining) cross-sectional dependence and strong dependence on a dominant region (which is rejected later from the data at the level of aggregation used in the analysis). Second, applying this framework to estimate and forecast the spatial co-development of regional labour markets, we examine the information content of several economically prospective as well as non-economical indicators.

Recent research has found improvements in univariate forecasts on regional labour market quantities when accounting for space-time dynamics. E.g., Longhi/Nijkamp (2007) forecast

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1 For example, the unemployment forecasts of the Institute of Employment Research (IAB) and the German Federal Employment Agency shifted from the pre-crisis prediction for 2009 (Aug. 2008) of 3.16 mio over 3.3 mio in the early crisis (Oct. 2008) to 3.6 mio (Feb. 2009), and saw unemployment reaching 4.1 mio in 2010 (Summer 2009). Roughly at the same time (June 15 2009), 'Deutsche Bank'-economist Norbert Walter predicted unemployment to exceed 5 mio in 2010, to our knowledge the most pessimistic forecast for Germany.

2 The growth rate according to the German Federal Statistical Office published on January 13th 2010 mounts to -5%.

3 `http://www.nytimes.com/2010/02/12/business/economy/12usecon.html`, accessed Nov. 16th, 2012

local employment under consideration of contemporaneous spatial dependence. In Hampel et al. (2008) and Schanne/Wapler/Weyh (2010) serially lagged spatial dependence contributes to a higher forecast accuracy in employment and unemployment, respectively. Mayor/Patuelli (2012) employ a Spatial VAR (SpVAR) and a Spatial-Filter based dynamic heterogeneous coefficient model (SF-GWR) to predict unemployment; they argue that the SpVAR is advantageous when forecasting in long data with a small cross-sectional dimension, and that the SF-GWR forecast performance becomes relatively better with a shorter observation period or increasing number of regions. However, recently techniques became available that allow on the one hand for a certain variability of other variables' impacts across the regions, and on the other hand provide a more distinct view on the cross-dependence of regions by discussing the conditions for either strong or weak cross-sectional dependence (Pesaran/Tosetti, 2007; Chudik/Pesaran, 2011; Chudik/Pesaran/Tosetti, 2011). Cross-sectionally weak dependence is defined as correlation patterns which arise in a certain group of series and which do not extend towards series not included in this group. An example is spatial autocorrelations where the degree of cross-sectional dependence declines over space. In contrast, cross-sectionally strong dependence requires the existence of a series (a region) that is correlated with all other series in the system; these are considered to depend on this dominating series. This method has been developed for modeling a multinational monetary system (Pesaran/Schuermann/Weiner, 2004, Dees et al., 2007, Pesaran/Schuermann/Smith, 2009), hence it is denoted as Global VAR (GVAR). It is also employed to model the spatio-temporal diffusion of shocks on housing prices across regions and to forecast real-estate markets in the UK (Holly/Pesaran/Yamagata, 2011). To our knowledge, we are the first to adopt this method in a multivariate model of regional labour market development.

Once the baseline model has been established, further investigating the forecast content of the usual leading indicators is quite a natural exercise, of interest for two reasons. On the one hand, it might be possible that these indicators entail only information which develops simultaneously and which is already incorporated in the (local and spatially interdependent) labour market history itself: e.g., consumption or wholesale sentiments will be affected by aggregate disposable income which, in turn, will be affected by recent unemployment. If an indicator for consumption provides more prospective information than the recent development within the labour market is thus an empirical question, but so is the question whether small independent single region indicator models are more precise in forecasting than complex models with interdependent regions. On the other hand, most frequently employed leading indicators in both national and regional forecasting refer to sentiments or register-based information on the development of production or financial markets: Economic tendency surveys, stock-market indices, wholesale, new orders, etc. Further investigation of their forecast content regarding employment and unemployment stands to reason, given the somewhat broken relationship between production and labour markets. With regard to the information content of the usual leading indicators several questions may be raised: If (regional) labour markets have detached from GDP (or product markets), is the relation between labour and product markets weakened only temporarily or regionally, and has a new relation already formed? If the relation is broken, can expectations regarding product market developments still contribute to improve the forecast accuracy in labour markets?

And, are other indicators, beyond business expectations, available providing information regarding the future development of regional labour markets? We thus compare standard production and financial indicators with supposedly prospective indicators immanent to the labour market. Furthermore, we test another set of potential indicators which describe climate data. The idea for this results from the observation that both local employment and unemployment show extraordinary persistent shifts in particular in periods with abnormal weather phenomena, e.g. the mild winters in 2006/07 and 2007/08 – in these, unemployment did not show the usual seasonal increase at the end of the year, but a spring decline with normal size.

In this paper, we focus on the development of regional labour market quantities, (log) employment and (log) unemployment, at a monthly frequency, for which data is introduced in Section 2. Section 3 sketches theoretically the economic intuition behind the empirical model developed in Section 4. Here, the focus is on describing the Global VAR, an econometric approach that makes the two-variables multi-regional system of time series tractable. The identification of joint developments of the non-stationary series and the identification of a dominant region (or our failure to identify it) are of particular interest. Section 5 introduces the various indicators tested out in the subsequent forecasting exercise. The forecast accuracy of the models is discussed in Section 6 by evaluation of simulated out-of-sample forecasts for the ten regional subdivisions of the Federal Employment Agency (in size roughly equivalent to NUTS-1 regions). Indeed, in our setting, the prospective information regarding the labour market which is provided by business-cycle indicators turns out to be extremely limited, hardly exceeding the contribution some climate series can make to labour-market forecasting. In contrast, accounting for cross-sectional dependence improves the forecast accuracy in most of the tested specifications.

2 The Data and Their Statistical Properties

Information on labour-market quantities is provided at various regionally disaggregated levels by the German Federal Employment Agency (FEA, Bundesagentur fÃ¼r Arbeit). Our monthly series on unemployment and employment stem from register data, begin in January 1996 and are not seasonally adjusted. Unemployment covers all persons officially registered as unemployed: they receive unemployment benefits from the FEA, look for a job and are ready to take on a job. Employment covers all employees in full- and part-time jobs liable to social security contributions, reported at their workplace. The analysis is carried out at the level of the Federal Employment Agency's Regional Divisions (RD). These are equivalent or slightly larger than the German federal states, often entailing two smaller states. Some descriptive statistics and a stationarity analysis are provided in Table 1.

To highlight just a few details in the data, we first observe that the difference between the largest region, North Rhine-Westphalia, and the smallest regions, Saxony and Rhineland-Palatinate/Saarland, mounts to less than 1.5 log points – equivalent to NRW being approximately 4.5 times as large as the smallest regions, and not 20 times as we find it at the level of Federal States. That is, the RD series reflect indeed a rather homogeneous number of persons. Second, the average monthly change of log employment and log unemployment

Table 1: Descriptive Statistics and Unit root tests

	Levels (Y)		Differences (ΔY)		HEGY-tests		ADF-tests	
RD	Mean	St.Dev.	Mean	St.Dev.	$t_{(\pi_1)}$	$F_{(\pi_2-\pi_{12})}$	$t_Y^{(DF)}$	$t_{\Delta Y}^{(DF)}$
			Log unemployment, 1/1996–12/2011					
Nord	12.78	0.14	-0.00	0.04	-0.89	577.18	-1.42	-8.11
BB	13.07	0.14	-0.00	0.03	-0.25	607.79	-1.04	-9.02
Sat	12.90	0.24	-0.00	0.05	0.54	369.57	-0.39	-8.42
S	12.75	0.20	-0.00	0.04	0.38	494.11	-0.53	-8.08
BY	12.82	0.22	-0.00	0.07	-1.22	824.59	-1.64	-8.27
BW	12.63	0.17	-0.00	0.03	-2.15	1660.31	-0.55	-9.64
RPS	12.14	0.14	-0.00	0.04	-1.01	555.83	-1.20	-8.81
H	12.35	0.14	-0.00	0.03	-1.63	831.98	-0.89	-9.43
NRW	13.64	0.10	-0.00	0.02	-1.87	851.34	-1.04	-8.86
NSB	12.90	0.14	-0.00	0.04	-1.01	461.93	-1.24	-9.07
			Log employment, 1/1996–12/2011					
Nord	14.57	0.03	0.00	0.01	-2.26	1308.77	-1.47	-7.24
BB	14.44	0.05	-0.00	0.01	-1.72	1285.16	-1.89	-8.02
Sat	14.26	0.07	-0.00	0.01	-1.86	495.83	-1.87	-7.35
S	14.18	0.06	-0.00	0.01	-2.01	610.08	-1.88	-7.20
BY	15.29	0.04	0.00	0.01	-1.16	1040.44	-0.96	-8.90
BW	15.15	0.03	0.00	0.01	-1.54	1454.40	-0.55	-11.73
RPS	14.24	0.03	0.00	0.01	-1.74	682.84	-1.19	-9.15
H	14.58	0.03	0.00	0.01	-2.12	696.32	-0.98	-9.75
NRW	15.57	0.02	0.00	0.01	-2.21	981.57	-1.05	-9.76
NSB	14.80	0.03	0.00	0.01	-1.09	417.34	-1.17	-9.26

BB: Berlin & Brandenburg – BW: Baden-Wurttemberg – BY: Bavaria – H: Hesse – Nord: City of Hamburg, Mecklenburg-Western Pommerania, Schleswig-Holstein – NRW: North Rhine-Westphalia – NSB: City of Bremen & Lower Saxony – RPS: Rhineland-Palatinate & Saarland – S: Saxony – SAT: Saxony-Anhalt & Thuringia

HEGY-tests are carried out with seasonal dummies and a constant (without deterministic trend), see Beaulieu/Miron (1993). The critical values at the 5% level are -2.760 for the zero frequency and 4.490 for the joint test on the seasonal frequencies.

The ADF tests refer to deseasoned data. The critical value at the 5% level is -2.889, at the 1% level -3.507.

is almost zero in any region whereas the standard deviations of both the levels and the monthly differences are larger. Hence, we carry out the subsequently presented analyses without considering a deterministic linear trend. Third, furthermore, the reported ADF tests and HEGY tests always do not reject unit roots in the first lag (the zero frequency) at the 99 % significance level (and only in a few regions at the 95 % level), whereas non-stationarity at the seasonal frequencies and in the monthly-differentiated series are rejected; this finding is supported by other (not reported) unit-root tests. Thus, we consider all series to be integrated of order one, I(1). Shocks in the regional labour markets can be considered as persistent. Information on additional features of the data will be provided throughout the following sections, after the corresponding description of the estimation technique.

3 Regional labour-market dynamics: A sketch

The standard dynamics in a search-matching framework (see, for example, the textbook version of Cahuc/Zylberberg, 2004: Ch. 9.3) can be adapted in a multi-region model such that the unemployment change equation is

$$\begin{aligned}\Delta U_{i,t} &= \Delta N_{i,t} - \left[m(\theta_i)\,(1-a_i) + m(\theta_i^*)\,a_i\right] U_{i,t-1} \\ &\quad + \delta_i(1-a_i)L_{i,t-1} + \delta_i^* a_i L_{i,t-1}^* \qquad (1)\end{aligned}$$

where $U_{i,t}$ denotes unemployment in region i at time t. $N_{i,t}$ is the labour force (for simplicity, all entering persons are assumed to start as unemployed job-searchers, all retiring persons to leave from unemployment). Job-creation depends on the matching function $m(\theta)$ with $\theta = \frac{\text{vacancies}}{\text{unemployment}}$ the labour-market tightness observed at home θ_i or abroad θ_i^* and weighted with the probability to work at home $1 - a_i$ or to commute a_i. Likewise, $L_{i,t}$ is employment and the parameters δ_i the job-separation rate; an asterisk marks variables abroad. Analogously, the employment change equation is

$$\Delta L_{i,t} = -\delta_i L_{i,t-1} + m(\theta_i)\,(1 - a_i) U_{i,t-1} + m(\theta_i)\, a_i^* U_{i,t-1}^* \quad . \tag{2}$$

Stacking both equations, this can be written as

$$\begin{aligned} \begin{pmatrix} \Delta U_{i,t} \\ \Delta L_{i,t} \end{pmatrix} &= \begin{bmatrix} -m(\theta_i) - [m(\theta_i^*) - m(\theta_i)]a_i & \delta_i(1 - a_i) \\ m(\theta_i)\,(1 - a_i) & -\delta_i \end{bmatrix} \begin{pmatrix} U_{i,t-1} \\ L_{i,t-1} \end{pmatrix} \\ &+ \begin{bmatrix} 0 & \delta_i^* a_i \\ m(\theta_i)\, a_i^* & 0 \end{bmatrix} \begin{pmatrix} U_{i,t-1}^* \\ L_{i,t-1}^* \end{pmatrix} + \begin{pmatrix} \Delta N_{i,t} \\ 0 \end{pmatrix} \quad . \end{aligned} \tag{3}$$

Note that the structure of this model is similar to a first order VEC model. Post-multiplying (3) with $\begin{pmatrix} {U_{i,t-1}}^{-1} & 0 \\ 0 & {L_{i,t-1}}^{-1} \end{pmatrix}$ results in a model for the log growth rates (or the difference of the logs) depending on the ratio of previous unemployment at home and abroad, the matching rates and the job-separation rates at home and abroad which can be assumed to be affected by, for example, the business cycle or labour market policy. The model in logs would moreover contain an approximately linear relationship $\ln L_{it}^* - \ln L_{it}$ included in the unemployment equation (as long as job separation is considered exogenous); supposedly, it won't be possible to derive a linear relationship containing unemployment because it is included also in the definition of labour-market tightness.

4 Specifying a system of regional labour markets

4.1 The Global VAR formulation

Vector Autoregressions (VAR) are the starting point for forecasting multiple interdependent time-series in a Global VAR model. Let $y_{i,t}$ denote the $m \times 1$ vector of target variables for region $i \in \{0, \ldots, n\}$ (here, $y_{i,t} = (\ln U_{i,t}, \ln L_{i,t})'$ with $m = 2$). The vector $\xi_{it} = B_i x_{i,t}$ contains the contribution regarding unemployment's and employment's development provided by indicators $x_{i,t}$ available at time t (observed before t), and B_i the matrix of parameters corresponding to these indicators. For notational simplicity, $\xi_{i,t}$ entails the deterministic mean (modeled by a constant plus seasonal dummies and, for the estimations with a sample ending after June 2005, additionally by a dummy variable for the pre-2005 period in order to account for the structural break due to the 2004/2005 labour-market reforms in Germany) as well. Let $\mathbf{Y}_t = (y_{0,t}', \ldots, y_{n,t}')'$, $\mathbf{\Xi}_t = (\xi_{0,t}', \ldots, \xi_{n,t}')'$, and $\mathbf{\Upsilon}_t$ the random error vector. Φ_ℓ is the coefficient matrix corresponding to lag $\ell = \{1, 2\}$; lag order 2 corresponds to the lag order determined to be optimal in region-specific VARs with seasonal dummies coincidentally according to the three information criteria of Akaike, Schwartz, and

Hannan/Quinn (AIC, BIC, and HQIC), which should be sufficiently large even for a multi-regional VAR. Then, a VAR over all regions can be written as

$$\mathbf{Y}_t = \Phi_1 \mathbf{Y}_{t-1} + \Phi_2 \mathbf{Y}_{t-2} + \mathbf{\Xi}_t + \mathbf{\Upsilon}_t, \tag{4}$$

or, rewritten in VEC form with $\Pi = (\Phi_1 + \Phi_2 - I_{m \times n})$ and $\Gamma = -\Phi_2$, as

$$\mathbf{\Delta Y}_t = \Pi \mathbf{Y}_{t-1} + \Gamma\, \mathbf{\Delta Y}_{t-1} + \mathbf{\Xi}_t + \mathbf{\Upsilon}_t \quad . \tag{5}$$

These equation systems are not estimable unrestrictedly unless the number of regions is extremely small since the number of the coefficients in the square matrices Φ_1, Φ_2 and the residuals' covariance matrix $\Sigma_{\mathbf{\Upsilon}}$ grows quadratically, with a rate of n^2 (and m^2). The idea of a GVAR is the following: To impose restrictions, we use the location and the corresponding information on geographical proximity between regions. This information allows the aggregation of the observable or predetermined information. Moreover, it allows to aggregate most of the unobservable simultaneous movement in the system (the correlated residuals) to a component which, under some additional assumptions discussed below, converges towards zero. Then, the system (4) or (5), respectively, can be split into partitions which may be considered independent from each other in an econometric sense and, hence, may be estimated partition-by-partition.

We assume analogously to Pesaran/Schuermann/Weiner (2004) that most regions contribute only little to explaining labour market development in other regions, relative to the joint influence of all other regions; as an aggregate, however, they may have a non-negligible impact. The labour market in region i can be considered to depend on the one hand on a important, dominant or leading region whose influence should be modelled explicitely[4], and on the other hand on a weighted average over the non-dominant regions instead of the particular development of each region $j = \{0, 1, \ldots, i-1, i+1, \ldots, n\}$. Variation in the strength of dependence across regions can be modeled by various predetermined or exogenous metrics for proximity between regions i and j. These weights $w_{ij,k}$ may reflect geographical, cultural, social or economical distance (see Conley/Topa, 2002; Corrado/Fingleton, 2012 and, for the pros and cons of different weights, the comments on Pesaran/Schuermann/Weiner, 2004 in the respective volume of the JBES).

Assumption 1 (Spatial weights in a GVAR). *Let matrix $W_{(N)}$ entail the sequences of weights in $w_{ij,k}$ (combined across variables $k = 1, \ldots, m$ and regions $i = 0, \ldots, n$). $W_{(n)}$ satisfies a number of "smallness" or "granularity" conditions (see Chudik/Pesaran/Tosetti, 2011): that its spectral norm (the Euclidean matrix norm) is bounded by a sequence converging with rate $\frac{1}{\sqrt{n}}$ or faster to a constant, i.e. $\|W_{(n)}\|_2 = [\max_k \lambda_{(W_{(n)} W'_{(n)})}]^{1/2} = O(\frac{1}{\sqrt{n}})$, and that $\frac{w_{ij,k}}{\|W_{(n)}\|_2} = O(\frac{1}{\sqrt{n}})$. These conditions hold if the row and column norms, i.e. $\|W_{(n)}\|_1 = \sup \sum_{i=0}^{n} |w_{ij,k}| \leq c$ and $\|W_{(n)}\|_\infty \sup \sum_{j=0}^{n} |w_{ij,k}| \leq c$, are bounded in absolute value (a standard assumption in spatial econometrics).*

[4] Examples for dominant units are London for the UK or Paris for France. Other countries like the US have a multi-core structure without a region (state, Metropolitan Area) that dominates the country as a whole. For Germany, ex ante, North Rhine-Westphalia (with the Ruhr area, Germany's largest agglomeration, and the one-million-inhabitant city of Cologne) could be considered a natural candidate for being dominant; however, other regions have similar size and economic power, hence a multipolar structure (without clear dominance structure) is possible as well.

Different weights can be employed for different variables (indexed with k), although typically the same weights are applied for all m elements of the vector $y_{i,t}$. We define the $m \times m$ matrix block $w_{ij} = w_{ij,k} I_m$, using the elements of a row-standardized contiguity matrix as weights in our empirical application (due to standardisation the row sums are always unity). These weights are used to construct the *local average* corresponding to region i (i.e. the weighted average over all "non-domestic" regions or, in other words, the spatial lag), subsequently denoted with $y_{i,t}^* = \sum_{j=0}^{n} w_{ij} y_{j,t}$. With granular weights, the local average can not be implicitly dominated by any single region.

The dominant region (and its history) drives the development of all other regions (series). It behaves, as it has been discussed by Pesaran/Tosetti (2007) and Chudik/Pesaran/Tosetti (2011), similar to a factor f_t in a dynamic factor model with mutual cross-sectional dependence (see also Stock/Watson, 2011, for an overview, and for factor methods using (dynamic) principal components Forni et al., 2000, 2005; Bai/Ng, 2002; Peña/Poncela, 2004):

$$y_{i,m,t} = \theta_{i,m} f_t + v_{i,t} \tag{6}$$

for $i = 1, \dots, n$, with $\theta_{i,m}$ the vector of factor loadings which relate the common factor (or the dominant region) to the dependent variable and $v_{i,t}$ the idiosyncratic component. Non-dominant regions may show cross-sectional correlation with regard to their idiosyncratic part; however, this mutual dependence is too weak to form a distinct factor pattern which loads on all regions.

Let c_i denote the parameter matrix describing the contemporaneous dependence of region i on the innovation in the dominant region 0, i.e. the 'factor loadings'; $C_0 = (0_{m \times m}, c_1', \dots, c_n')'$ is the $[m(n+1) \times m]$ matrix of loadings. Then, we can assume for the error covariance matrix that

$$\Sigma_{\Upsilon_t} = R^{-1\prime} \begin{pmatrix} \sigma_0^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_1^2 & \sigma_{1,2} & \cdots & \sigma_{1,n} \\ 0 & \sigma_{2,1} & \sigma_2^2 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \sigma_{n-1,n} \\ 0 & \sigma_{n,1} & \cdots & \sigma_{n,n-1} & \sigma_n^2 \end{pmatrix} R^{-1} \quad , \tag{7}$$

with $R = [I_{m(n+1)} - (C_0, 0_{m(n+1) \times mn})]$, $\sigma_{ij} = E(\varepsilon_i \varepsilon_j')$ the system cross-covariance between regions i and j, σ_i^2 the variance-covariance of the system within region i. Whereas for all non-dominant regions the errors may be interdependent, the dominant region is considered to be stochastically independent from the other regions. Thus, its development can be included contemporaneously as (weakly) exogenous variable in partial systems regarding other regions.

Granularity of the weights ensures that the covariance between the disturbance and its local average is bounded as $n \to \infty$:

$$E(\varepsilon_{it} \varepsilon_{it}^{*\prime}) = E(\sum_{j=0}^{n} \varepsilon_{it} \varepsilon_{jt}' w_{ij}') = \sum_{j=0}^{n} E(\varepsilon_{it} \varepsilon_{jt}') \|W_n\| \frac{w_{ij}'}{\|W_n\|}$$

$$= \sum_{j=0}^{n} \sigma_{ij} O(\tfrac{1}{\sqrt{n}}) O(\tfrac{1}{\sqrt{n}}) \leq \sum_{j=0}^{n} \tfrac{1}{N} \sigma_{ij} \quad . \tag{8}$$

The variance-covariance of the local average converges towards zero as $n \to \infty$:

$$E(\varepsilon^*_{it}\varepsilon^{*\prime}_{it}) = E(\sum_{j=0}^{N} w_{ij}\varepsilon_{jt}\varepsilon'_{jt}w'_{ij}) \leq \tfrac{1}{N^2} \sum_{j=0}^{N} O(1)\sigma_j^2 \to 0 \quad . \tag{9}$$

Hence, under granularity of weights, the local average can be considered as asymptotically (weakly) exogenous.

Utilizing weak exogeneity of the local averages, the cross-regional equation system (5) – the VEC form is used here for convenience – is divided into only weakly dependent blocks of equations. The vector $y_{0,t}$ is included separately in the systems for all other regions, whereas the non-dominant units are accounted for through $y^*_{i,t}$. Then, the system for the labour market (unemployment and employment) in a single region becomes

$$\begin{aligned}\Delta y_{i,t} = h_i y_{i,t-1} + h^*_i y^*_{i,t-1} + h^0_i y_{0,t-1} + g_i \Delta y_{i,t-1} + g^0_i \Delta y_{0,t-1} + g^*_i \Delta y^*_{i,t-1} \\ + \mu_{i,t} + c_i \Delta y_{0,t} + \varepsilon_{i,t} \quad .\end{aligned} \tag{10}$$

For the dominant region itself (for $i = 0$) or, if there is no dominant unit for all regions, a region-specific equation system can be extracted as

$$\Delta y_{i,t} = h_i y_{i,t-1} + h^*_i y^*_{i,t-1} + g_i \Delta y_{i,t-1} + g^*_i \Delta y^*_{i,t-1} + \mu_{i,t} + \varepsilon_{i,t} \quad . \tag{11}$$

By defining $\mathbf{w}_i = (w_{i0}, \ldots, w_{iN})'$ and

$$G = \begin{pmatrix} g_0 & 0 & 0 & \cdots & 0 \\ g^0_1 & g_1 & 0 & \cdots & 0 \\ g^0_2 & 0 & g_2 & \ddots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ g^0_N & 0 & \cdots & 0 & g_N \end{pmatrix} + \begin{pmatrix} g^*_0 \mathbf{w}'_0 \\ g^*_1 \mathbf{w}'_1 \\ g^*_2 \mathbf{w}'_2 \\ \vdots \\ g^*_N \mathbf{w}'_N \end{pmatrix},$$

$$H = \begin{pmatrix} h_0 & 0 & 0 & \cdots & 0 \\ h^0_1 & h_1 & 0 & \cdots & 0 \\ h^0_2 & 0 & h_2 & \ddots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ h^0_N & 0 & \cdots & 0 & h_N \end{pmatrix} + \begin{pmatrix} h^*_0 \mathbf{w}'_0 \\ h^*_1 \mathbf{w}'_1 \\ h^*_2 \mathbf{w}'_2 \\ \vdots \\ h^*_N \mathbf{w}'_N \end{pmatrix},$$

stacking the region specific systems (11) and (10) gives, here again for the case of a single dominant region, a structural VEC over all regions:

$$R\mathbf{\Delta Y_t} = H\mathbf{Y_{t-1}} + G\mathbf{\Delta Y_{t-1}} + \mu_\mathbf{t} + \varepsilon_\mathbf{t}. \tag{12}$$

System (5) follows from $\mathbf{\Upsilon_t} = R^{-1}\varepsilon_\mathbf{t}$, $\Pi = R^{-1}H$, $\Gamma = R^{-1}G$ and $\mathbf{\Xi_t} = R^{-1}\mu_\mathbf{t}$. Solve backward with $\Phi_1 = (\Pi + \Gamma - I_{m(n+1)})$ and $\Phi_2 = -\Gamma$ to get the VAR described in system (4). The unit-specific systems given by eqs. (10) and (11) can be estimated region-by-region. Since the number of parameters per region-specific partial system is limited, the estimations are computationally tractable. What needs to be answered ex-ante is on the one hand which regions share common stochastic trends, on the other hand whether there is one (or more than one) dominating region, and if so, which regions are dominant.

4.2 Regional dominance in cross-sectional dependence

We start the discussion on the strength of cross-sectional dependence from a dynamic-factor perspective since a dominant region can be considered as a strong factor. Suppose [as in eq. (6)] that each series $y_{i,m,t}$ in $\mathbf{Y}_t$ can be separated additively into a component $\chi_{i,m,t} = \theta_{i,m} f_t$ which entails the co-evolution of the series due to a small number of common factors f_t and an idiosyncratic component $\upsilon_{i,m,t}$. The factor space is spanned by the (dynamic) principal components of the systems variance-covariance matrix $\Sigma_{(Y)t}$. Principal Component Analysis (PCA) allows to determine a standardized orthogonalization of the factor space; the factors themselves might be represented by any rotation of the factor space (Forni et al., 2000). The dimension of the factor space (the number of factors r) equals the number of diverging eigenvalues of $\Sigma_{(Y)t}$. Research using PCA frequently employs the number of eigenvalues exceeding one in absolute value as a criterion. Several studies (e.g. Bai/Ng, 2002) establish information criteria penalizing each additional factor in order to test for the number of factors. Here, we use the procedure presented by Onatski (2010) which, though still overestimating the number of factors in small cross-sections, tends to perform better than many information criteria. The number of factors according to standard PCA and to the Onatski-Criterion are, besides other statistics described below, reported in Table 2. We show numbers for the original I(1) series (Y), for series filtered for deterministic seasonal means ($Y - \bar{Y}_s$), for the (stationary) first differences of the seasonally filtered series ($\Delta[Y - \bar{Y}_s]$) and for series filtered for spatial auto-correlation (that is, weak dependence) ($[I - \rho W]Y$), because the findings may be sensitive to joint deterministic components, non-stationarity and mutual correlation of the idiosyncratic components.

In the traditional factor literature, the diverging (factor-related) eigenvalues increase linearly in the cross-sectional dimension, that is with a rate equal to n, whereas the remaining eigenvalues are bounded and independent from the cross-sectional dimension. As a consequence, statistical criteria for the identification of factor structures test for divergence vs. non-divergence of the eigenvalues while neglecting their actual rate of divergence (e.g. Bai/Ng, 2002). Chudik/Pesaran/Tosetti (2011) have introduced a concept of semi-strong (or semi-weak) factors associated with eigenvalues that increase less than linearly, at a rate of $O(n^{1-\epsilon})$ with $\epsilon \in (0,1)$. Semi-strong and semi-weak factors affect only a limited number of regions/series but not all, or are related with every region with a strength of relation declining at a rate faster than $\frac{1}{n}$.[5] Semi-strong or weaker factors generate only cross-sectionally weak dependence – similarly to those correlation patterns that are considered $O(1)$, that is non-increasing with the cross-sectional dimension. For the existence of a dominant region in a GVAR model it must however hold – as for any model with at least one strong factor – that the first (maximum) eigenvalue diverges linearly, i.e. that $\max \lambda_{(\Sigma_{Y_t|\mathcal{I}_t, w_{(n)}})} = O(n)$. Hence, to identify or reject regional dominance, we have to determine the exponent $(1 - \epsilon)$ in the order of divergence.

Bailey/Kapetanios/Pesaran (2012) propose estimators to determine the order of divergence

[5] In the words of Chudik/Pesaran (2013), p. 15: "...that affects only a subset of the units and the number of affected units rise more slowly than the total number of units." Formally, a factor is strong if all factor loadings are bounded away from zero, $|\theta_{i,m}| > 0$. A semi-strong factor requires that, for some i, m, the loadings are not bounded away from zero.

of the largest eigenvalue (here denoted with $O(n^{\alpha})$) in a system of equations; we employ the first-order bias corrected version $\tilde{\alpha}$. The procedure follows the intuition that, within a system of n equations, αn series are strongly cross-sectionally dependent whereas the remaining are independent (or at most weakly dependent) from the others; strong cross-dependence results from factor loadings (with a single factor) which are bounded away from zero. In this setting, the largest eigenvalue of the system's variance-covariance matrix has to increase at order n^{α}. The estimator has the main advantage that its distribution has been established analytically; this allows to test the order of divergence against lower and upper thresholds, albeit at a very low rate of convergence ($\ln n$). However, it does not fit perfectly to our analysis: On the one hand, the procedure employs only the overall system covariance matrix and the proportion of this covariance assessable to the first factor. On the other hand, those regions which are not strongly dependent are considered as uncorrelated (in contrast to being weakly dependent). A fraction of strongly correlated units and a complementary fraction of independent units do not match the spatial structure where the degree of dependence declines continuously in the distance. Finally, the maximum number of neighbours which a single region has in our case is six (of nine possible regions); hence, the lower threshold which describes only weak (spatial) correlation is at least in the univariate partial systems (only unemployment, only employment) extremely high.

Thus, as an alternative we try to estimate the exponent in $O(n^{1-\epsilon}) = n^{1-\epsilon}O(1)$ from randomly determined partial systems with varying size, an approach which has not been pursued before and of which the statistical properties have not been proven yet. For each possible number of regions $n \in 2, \ldots, n$, we randomly draw 50 subsystems (without replacement, i.e. without including the same series twice). We retain the largest eigenvalue of the corresponding variance-covariance matrix $\lambda_{max,(n),j} = \max \lambda_{(\Sigma)}$ and the size of the system n_j for each iteration j. Then, we estimate the equation

$$\ln(\lambda_{max,(n),j}) - \ln(n)_j = -\epsilon \ln(n)_j + c + \nu_j \qquad (13)$$

to determine the parameter ϵ in the eigenvalues' order of divergence. If the estimate $-\hat{\epsilon}$ is significantly[6] negative, we can conclude that the eigenvalues diverge at a less than linear rate.

Results for the cross-regional systems of unemployment, employment and the two variables jointly together are provided in Table 2, differentiated by the two sampling periods and the various filters. PCA suggests throughout all filters and sampling periods three to four factors in the whole system of twenty equations. Two factors are inherent to the employment subsystem and one to three factors exist in the unemployment subsystem. That is, according to PCA it is likely that one factor affects both variables jointly whereas there exist also factors specific to unemployment and employment. The Onatski criterion is much more restrictive: when taking the unfiltered, the seasonally filtered and the monthly-differentiated series into consideration, it suggests that only one factor exists which affects

[6] The 'population' of series in our case is small, and so is the number of candidate eigenvalues. Eigenvalues are Tracy-Widom distributed (Tracy/Widom, 1994; Onatski, 2009). Thus, since inference may be non-standard, critical values have been derived by simulation. Critical values for the hypothesis $H_0 : -\epsilon \geq 0$ are provided in Table 10 in the appendix to this chapter, together with the code for the simulation.

Table 2: Rate of divergence and factor structure in spatially filtered series

Statistic	Filter	$U_1,\dots,U_N,L1,\dots,L_N$		$U_1,\dots,U_N$		$L,\dots,L_N$	
		2005	2011	2005	2011	2005	2011
r (PCA)	Y	3	3	2	2	2	2
r (Onatski)		1	1	1	1	1	1
$\hat{\epsilon}$		0.099	0.062	0.116	0.043	0.181	0.172
		(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
$\tilde{\alpha}$		0.653	0.755	0.958	0.986	0.930	0.938
		(0.92)	(0.33)	(0.14)	(0.11)	(0.08)	(0.09)
r (PCA)	$Y-\bar{Y}_s$	3	3	2	1	2	2
r (Onatski)		2	1	1	1	2	2
$\hat{\epsilon}$		0.116	0.078	0.117	0.041	0.199	0.193
		(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
$\tilde{\alpha}$		0.639	0.758	0.949	0.985	0.927	0.933
		(1.84)	(0.31)	(0.18)	(0.46)	(0.08)	(0.10)
r (PCA)	$\Delta(Y-\bar{Y}_s)$	4	4	2	2	2	2
r (Onatski)		1	1	1	1	2	1
$\hat{\epsilon}$		0.155	0.157	0.108	0.100	0.206	0.169
		(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
$\tilde{\alpha}$		0.825	0.837	0.962	0.969	0.921	0.940
		(0.23)	(0.34)	(0.04)	(0.03)	(0.09)	(0.06)
r (PCA)	$(I-\rho W)Y$	3	3	3	3	2	2
r (Onatski)		2	0	0	0	1	1
$\hat{\epsilon}$		0.218	0.168	0.257	0.155	0.119	0.121
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\tilde{\alpha}$		0.623	0.691	0.883	0.945	0.827	0.848
		(0.34)	(0.37)	(0.13)	(0.11)	(1.47)	(0.54)

Data filtered for spatial autocorrelation using Kapoor/Kelejian/Prucha (2007) estimates applied after a dynamic panel regression with homogeneous AR(1); for unemployment $\hat{\rho}=.5450$, for employment $\hat{\rho}=.6593$.

both employment and unemployment together. If we filter the data for spatial autocorrelation, it rejects the existence of a factor in the unemployment subsystem and, in the longer observation period, even in the complete system.

All estimates of the exponent in the order of divergence achieved in the subsystems $U_1,\dots,U_N$ and $L_1,\dots,L_N$ reject that the series are independent: $\tilde{\alpha}$ is always significantly above 0.5; $\hat{\epsilon}$ is in all tests smaller than one. Moreover, the estimates $\tilde{\alpha}$ suggest an exponent larger than 0.9 in the two subsystems with all filters except the one eliminating spatial correlation; an exponent of one, i.e. cross-sectionally strong dependence, is not rejected in any of these specifications. In contrast, $\tilde{\alpha}$ is much lower when estimated from the complete system, with standard errors so large that neither strong dependence nor independence can be rejected. The estimates $\hat{\epsilon}$ in the unemployment subsystem hint in the same direction as the estimates $\tilde{\alpha}$, rejecting strong dependence only if we eliminate weak dependence before. In the employment subsystems, perfectly strong dependence can be rejected at the usual significance levels. The estimates for ϵ achieved when sampling from all regional variables are in general in between the estimates achieved in the employment and unemployment subsystems; the values for $-\hat{\epsilon}$ are significantly smaller than the 10% critical value for the case of strong dependence but not smaller than the 10% value under semi-strong dependence in Table 10. Hence, estimation of ϵ likewise suggests only semi-strong but not strong cross-sectional dependence.

4.3 Common Trends: Cointegration and nonstationary common factors

We have seen in Table 1 that regional employment and unemployment (in logs) can be considered as nonstationary series, integrated of first order $I(1)$.[7] In the following, we analyse if two (or more) series – unemployment and employment within a region, or the same variable across regions – have a joint nonstationary stochastic trend describing the long-run relationship between the variables; the adjustment to deviations from such a trend can be employed in order to improve the forecasts. Joint trends across the regions can arise in the relationship to a possible dominant region or be due to correlated persistent shocks on neighbouring regions. They can be incorporated in system (10) by restricting

$$\begin{aligned} h_i y_{i,t-1} + h_i^* y_{i,t-1}^* + h_i^0 y_{0,t-1} &= (h_i - \eta_i^0 - \eta_i^*) y_{i,t-1} \\ &+ \eta_i^0 \left(y_{i,t-1} + [\eta_i^{0+} h_i^0] y_{0,t-1} \right) + \eta_i^* \left(y_{i,t-1} + [\eta_i^{*+} h_i^*] y_{i,t-1}^* \right) \end{aligned} \tag{14}$$

where A^+ denotes the generalized inverse of reduced-rank matrix A. $(h_i - \eta_i^0 - \eta_i^*)$ describes a linear relationship between the series of region i in levels; that is, intra-region cointegration. $[\eta_i^{0+} h_i^0]$ describes a linear stationary relationship between region i and a potentially dominant region, $[\eta_i^{*+} h_i^*]$ is the linear stationary relationship between region i and the corresponding local average; η_i^0 and η_i^* are the corresponding loading matrices.[8] For cointegration between the series, the traditional approach to model common trends (Engle/Granger, 1987, Lütkepohl, 2005), the parameter matrices have to satisfy either $\mathrm{rk}\{(h_i - \eta_i^0 - \eta_i^*)\} > 0$, $\mathrm{rk}\{\eta_i^0\} > 0$, or $\mathrm{rk}\{\eta_i^*\} > 0$. Two (or more) series are considered to share a common trend if there exists a linear combination of the series that is stationary (integrated of order 0). In a small equation system, it suffices to determine the rank of Π (or H, respectively) since $\mathrm{rk}(\Pi)$ equals the number of cointegrating relations. However, we have to pursue another strategy since we are not able to estimate Π directly.

We have seen before that the entire structure of a GVAR model can be understood as a factor model. In these, joint stochastic trends can be generated by nonstationary factors. However, nonstationarity can even be inherent in the idiosyncratic components. This can be crucial for the identification of the factor space and the number of factors (in particular for the stationary factors). In addition, nonstationary idiosyncratic components may forestall the existence of stationary combinations of series although the series have a common stochastic trend, thus eliminating cointegration: $y_{i,m,t} - \beta y_{i',m,t} = (\theta_{i,m} - \beta\theta_{i',m}) f_t + \upsilon_{i,m,t} - \beta \upsilon_{i',m,t}$ and $(\beta = (\theta_{i,m})^{-1} \theta_{i',m})$ can be stationary only if both $\upsilon_{i,m,t}$ and $\upsilon_{i',m,t}$ are stationary. Bai/Ng (2004) argue that a factor model in first differences allows to track nonstationarity in the components:

$$\Delta y_{i,m,t} = \theta_{i,m} \Delta f_t + \Delta \upsilon_{i,m,t} \tag{15}$$

with $\Delta\chi_{i,m,t} = \theta_{i,m}\Delta f_t$ the difference of the common component, f_t the vector of factors and $\theta_{i,m}$ the loadings of the factors corresponding to variable m in region i. For I(1) variables $y_{i,m,t}$, the model in differences is stationary, and results from standard factor analysis

[7] As a consequence of the series being $I(1)$, matrix Π in equation (5) has less than full rank; its determinant is 0.

[8] This structure is equivalent to the frequently used $\alpha\beta'$ decomposition in cointegration analysis; see e.g. Lütkepohl (2005), Ch. 6.3.

become applicable. For any number of factors r, $\Delta f_{(r)t}$ and $\Delta \upsilon_{(r)i,m,t}$ can be retained from principal component analysis and used further in the *Panel Analysis of Nonstationarity in Idiosyncratic and Common Components* (PANIC) proposed by Bai/Ng (2004). In this analysis, the first (strongest) factor $f_{(1)t} = f_{(1)0} + \sum_{\tau=1}^{t} \Delta f_{(1)\tau}$ and all $\upsilon_{(r)i,m,t}$ are tested for unit roots by ADF-test, and the number of nonstationary common components can be determined from the entire system of factors by the MQ$_c$ statistics. We augment their procedure by testing the first factor for HEGY-type seasonal unit roots and unit roots with structural breaks in addition to the ADF test. Results for the *PANIC* tests (without linear trend) and for the determined number of factors are provided in Table 3.

Table 3: Nonstationarity in idiosyncratic and common components

	Full system ($\mathbf{Y}_t$)		Unemployment (U_t)		Employment (L_t)	
	2005	2011	2005	2011	2005	2011
Unfiltered series						
# factors, PCA	3	3	2	2	2	2
First factor I(1) (ADF)	Yes	Yes	Yes	Yes	Yes	Yes
# I(1) factors (MQ$_c$)	1	2	1	1	2	2
# I(1) idios. comp.	13	13	8	4	5	6
Series filtered for deterministic seasonal figure (season dummies)						
# factors, PCA	3	3	2	1	2	2
First factor I(1) (ADF)	Yes	Yes	Yes	Yes	Yes	Yes
# I(1) factors (MQ$_c$)	1	1	1	1	2	2
# I(1) idios. comp.	17	17	9	7	6	6
Cross-sec. dimension (N)	20	20	10	10	10	10

All numbers presented refer to unit roots rejected at the 90% confidence level. Tests are carried out without linear trend.

The presented results suggest that, given the existence of at least one common factor, nonstationary factors affect both log unemployment and log employment. Nonstationarity of the first factor can not be rejected at reasonable significance levels not only in the reported Augmented Dickey-Fuller tests but also if we account for a structural break in January 2005 or in February 2007, the latter suggested as a break date of the unemployment factor by the Zivot/Andrews (1992) unit-root test. According to the MQ_c statistic, we can reject nonstationarity of more factors in the entire system than in the employment subsystem. All in all, the occurrence of more than one nonstationary common factor can be rejected in most specifications.

When it comes to the idiosyncratic components, we can reject nonstationarity at the 90% confidence level of ADF tests only in seven of the twenty investigated untransformed series; their majority seems to have I(1) idiosyncratic components. If we additionally control for regular seasonal patterns (before decomposing the series in the common and the idiosyncratic components), evidence for nonstationary idiosyncratic components becomes even stronger as shown in the lower panel of Table 3. Hence, because most often one or two (but up to three) nonstationary components are inherent in each combination, it is unlikely that we find a stationary linear combination of the series.

To ascertain this, we investigate the existence of cointegration in small subsystems, that is in pairwise relations between two series, and in the relation between regional series and the corresponding local average. We split system (5) in small subsystems and determine the rank of the subsystem's elements of Π; the number of cointegrating relations equals the matrix rank (see Johansen, 1991, 1995). Results for some tests, using Johansen's trace testing procedure and critical values at the 95%-level, are reported in Table 4.

Table 4: Number of cointegrating relations per regional subsystem

RD	U_i, L_i		U_i, U_j		L_i, L_j		U_i, U_i^*		L_i, L_i^*	
	2005	2011	2005	2011	2005	2011	2005	2011	2005	2011
Nord	0	.	0	0	0	1	0	0	0	.
BB	0	.	0	0	0	3	0	0	0	0
SAT	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0
BY	0	0	0	1	0	1	1	0	0	0
BW	0	0	0	0	1	0	0	0	1	0
RPS	.	0	1	0	2	2	1	0	.	1
H	.	0	1	1	1	1	.	0	0	0
NRW	0	0	0	0	1	0	0	0	0	0
NSB	0	0	0	0	1	0	0	0	1	0

Reported results refer to the period from January 1996 to December 2005 and 2011, respectively. Tables using the 99% critical values and the Hannan-Quinn Information Criterium, results over other sampling periods (till Dec. 2007 and 2009) and for cointegration in three-region systems (instead of the two region systems in columns 4-7) are available from the corresponding author.

A dot represents a full rank of the subsystems matrix Π. This implies stationarity of all series in the subsystem which is neither consistent with the other results on cointegration (presented in the same line) nor with the unit-root tests in Table 1.

The second and third column in Table 4 report the cointegration rank of a bivariate intra-region VEC, entailing only unemployment and employment. Columns four to seven show, across the regions, the number of pairwise cointegration relations of the same variable in two regions; the maximum of possible relations would be nine (if the series in a region cointegrates with the series in every other region). Columns eight to eleven refer to cointegration between a series in region i and the corresponding local average. Interestingly, we find hardly any evidence for cointegration between unemployment and employment inside a region. Cointegration between pairs of regional unemployment, or between unemployment in region i and unemployment averaged over the surrounding regions is not supported in general. In contrast, employment seems to cointegrate across some regions, that is to form stationary linear combinations driven by the same trend. For the sampling period ending in December 2005, we have joint trends between Rhineland-Palatine/Saarland and both Baden-Wurttemberg and Hesse (two of its neighbours), and between Lower Saxony/Bremen and North Rhine-Westphalia. The cointegrating relations change with the sampling period: with data ending in 2011, we find Berlin/Brandenburg (in the East) cointegrating with Bavaria (in the South-East), Rhineland-Palatinate/Saarland (in the South-West) and North, but no evidence for cointegration with the Eastern German regions Saxony and Saxony-Anhalt/Thuringia. When analysing further periods, evidence for some of these relations vanishes, whereas cointegration relations between other pairs of regions become significant.

To put the previous findings in a nutshell: we have shown first that the series are unlikely to form stationary linear combinations across the regions and that we cannot employ a cointegration relation. Then, a full model in VEC form, i.e. including the series in lagged log-levels, will be misspecified with a (supposedly insignificant) I(1) term on the right hand. Probably, a system in first differences (i.e. a VEC under the explicit restriction that all elements in Π are zero) produces more accurate forecasts.[9] Second, we have found only

[9] Regarding the problem of uncertain cointegration when forecasting, Stock (2001: p. 578) argues: *"How-*

evidence for semi-strong cross-sectional dependence.

5 Selection and inclusion of indicators

This section focuses on the appropriate determination of the component $\xi_{i,t}$ in equation system (11). It entails seasonal dummies, a dummy for the pre-2005 period (to account for the important labour-market reforms), and additionally the information provided by leading indicators. Often it is argued that the inclusion of a small number of indicators with a high information content performs better in forecasting than a larger number of indicators with less information (see e.g. Stock, 2001 or, especially for Germany, Gaggermeier, 2006).

To approximate the business cycle expectations, we use a set of publicly available national indicators: series of the Stock Market Index (DAX, at the end of a month), and the Wholesale Index provided by the German Federal Bank[10]; in particular the value of the major German enterprises and the sales within the economy can be considered as easily observable metrics regarding economic prospects. Alternatively, we use judgemental indicators regarding business situation and expectations (two indicators gained from a survey amongst financial experts, provided by the ZEW Centre for European Economic Research Mannheim[11]; two from a management survey, provided by the ifo institute Munich[12]).

In addition, we test the information content of some labour market series on vacancies and participants in a number of active labour-market policy (ALMP) programmes; the series are register data collected by the German Federal Employment Agency (FEA) at the same regional level as the employment and unemployment series. The metric of vacancies covers all job offers that are reported to the FEA. It underestimates the real number of job offers, though it may still serve as a prospective indicator. The measure for ALMP participation includes participants in job-training schemes and other programmes for which participants are counted neither as employed nor as unemployed. Thus, persons benefitting from subsidies employment are not included in this metric. ALMP programmes reduce the reported number of unemployed – during the programme, participants have reduced search activity and often are not able to take on a job instantaneously. Thus, approximately contemporaneous numbers on ALMP may reduce unexplained fluctuations in unemployment and help fitting the model. As well, it may be that unemployed persons benefit more from wage subsidies during a cycles upturn (or an expanding labour market), and relatively more from training programmes and their long-run effects during a economic contraction. Shifts in the number of training schemes may be related with the business cycle.

To measure the effect of climate (which seems interesting in the light of unemployment's

ever, even if cointegration is correctly imposed, it remains to estimate the parameters of the cointegrating vector, which are, to first-order, estimated consistently (and at the same rate) if cointegration is not imposed. If cointegration is imposed incorrectly, however, asymptotically biased forecasts with large risks can be produced."

[10] See `http://www.bundesbank.de/statistik/statistik_zeitreihen.php`, series BBK01.WU3140 (DAX) and M.DE.N.I.IT2.ACM01.V.I (Wholesale Index); accessed last 03.12.2012.

[11] See `ftp://ftp.zew.de/pub/zew-docs/div/konjunktur.xls` (accessed last 30.11.2012).

[12] The series Geschäftsbeurteilungen (R5) and Geschäftserwartungen (R6) are available at `http://www.cesifo-group.de/ifoHome/facts/Time-series-and-Diagrams/Zeitreihen/Reihen-Geschaeftsklima-Deutschland.html`, last accessed 30.11.2012.

development during the warm winters 2006 and 2007), we use a set of publicly available metrics on temperature, sun-shine, wind force and precipitation collected by the German Climate Service (Deutscher Wetterdienst) at 40 stations all over Germany[13]. We use minimum Temperature within a month (`tnn`), cloud amount (`nmm`), total monthly precipitation (`rss`) and average windforce (`fmm`). The climate indicators are averaged over those stations located within the territory of each RD to receive the region-specific value.

Most series are available over the whole sampling period starting in January 1996 (or even before). An exception are the metrics on vacancies and ALMP participants firstly reported in the FEA data in January 2000. Each indicator becomes available at the same (or with less) delay as the target series. In a number of unit-root tests analogously to those provided for the target variables in Table 1, the climate variables all show up to be stationary, whereas business-cycle indicators as well as ALMP-participation and vacancies supposedly contain unit roots. We account for this by analysing and including the non-stationary leading indicators in first differences.

Uncertainty in the h-step ahead predictor $\hat{\xi}_{i,T+h} = E(x_{i,T+h|T})\hat{\beta}$ stems from two sources, uncertainty about the value of the indicator $x_{i,t+h}$ and uncertainty about the relationship between $x_{i,t+h}$ and $y_{i,t+h}$ which is described by the parameter vector β. A good indicator is, on the one hand, significantly correlated with the variable of interest. Here, the temporal lead of an indicator is crucial: the same indicator variable may show high correlation with the target variable at a certain lead, and weak correlation at other leads. On the other hand, it should have a certain temporal lead to the variables of interest, such that the relevant observations of the indicator have realized already or, to be more precise, are observed with sufficient accuracy (with little measurement error) in the period when the forecast is made. Inaccurate observation of the indicator and data underlying major revisions increase the uncertainty in the model (for the discussion on data revisions and real-time forecasting see e.g. Jacobs/van Norden, 2011). Hence, the forecast variance will be smaller if the indicator's values are known. Nevertheless, the time delay between indicator and target variable should not be too large to be economically reasonable.

To restrict the number of relations tested out, we determine for each indicator the correlation with log employment and, respectively, log unemployment shown at any lead between zero and thirty-six months (or, due to the shorter observation period, twenty-four months for ALMP and Vacancies). Ordering the correlation according to their absolute values allows us to determine the optimum lead, i.e. the time delay for which the mostly significant relation with regional employment or unemployment can be expected. In general, there is no clear timing for the peak in the degree of correlation between two variables. Thus, we determine for each indicator-(un)employment-region combination the three leads with the highest correlation, which are shown in Table 5.

[13] See `http://www.dwd.de/bvbw/appmanager/bvbw/dwdwwwDesktop?_nfpb=true&_pageLabel=_dwdwww_klima_umwelt_klimadaten_deutschland`, last accessed 30.11.2012.

Table 5: Lead of the indicator variables, in months

	Nord	BB	SAT	S	BY	BW	RPS	H	NRW	NSB
Leads related with Δ unemployment										
Δ dax	29, 17, 5	28, 5, 29	4, 5, 16	29, 5, 4	28, 4, 5	5, 21, 11	5, 29, 28	5, 29, 17	28, 29, 16	28, 5, 29
Δ wholesale	36, 12, 24	36, 12, 24	36, 12, 24	36, 12, 0	36, 12, 24	36, 12, 24	36, 24, 12	36, 24, 12	36, 24, 12	36, 12, 24
Δ ifo-sit.	5, 7, 4	30, 28, 11	29, 30, 1	29, 30, 1	7, 28, 4	7, 4, 5	5, 29, 7	28, 5, 7	29, 7, 4	30, 28, 29
Δ ifo-exp.	36, 8, 0	0, 24, 36	0, 36, 24	24, 36, 0	0, 2, 4	0, 9, 8	36, 24, 0	36, 24, 0	36, 26, 0	26, 29, 2
Δ zew-sit.	10, 11, 3	10, 22, 11	34, 11, 23	34, 11, 10	10, 11, 22	5, 10, 11	10, 29, 11	10, 29, 11	10, 11, 29	10, 23, 22
Δ zew-exp.	27, 0, 15	27, 26, 36	27, 15, 3	3, 15, 27	14, 15, 27	0, 14, 15	27, 26, 15	27, 15, 0	26, 27, 2	26, 27, 2
Δ almp	0, 12, 1	0, 12, 16	4, 0, 16	1, 4, 16	0, 12, 24	12, 24, 0	0, 12, 24	0, 12, 6	0, 6, 12	7, 0, 6
Δ vacancies	3, 15, 2	11, 10, 23	2, 14, 10	2, 14, 1	2, 14, 1	2, 3, 15	2, 3, 11	11, 23, 2	11, 23, 2	2, 11, 10
fmm	7, 4, 6	31, 36, 35	31, 30, 29	36, 35, 25	5, 4, 7	4, 3, 5	4, 3, 5	25, 23, 24	3, 4, 2	23, 33, 25
nmm	24, 25, 26	3, 0, 2	32, 35, 31	0, 2, 3	2, 3, 4	26, 25, 27	25, 24, 23	25, 24, 26	25, 24, 26	3, 2, 4
rss	11, 10, 9	36, 35, 25	0, 8, 7	18, 19, 20	10, 11, 36	19, 36, 20	8, 10, 5	8, 19, 18	11, 10, 19	23, 28, 25
tnn	12, 11, 17	27, 28, 26	8, 9, 20	31, 20, 32	0, 10, 9	10, 9, 8	10, 11, 9	18, 11, 10	10, 11, 22	27, 28, 26
Leads related with Δ employment										
Δ dax	36 , 16 , 4	29 , 5 , 36	16 , 29 , 4	16 , 5 , 29	29 , 5 , 16	36 , 29 , 17	16 , 36 , 4	36 , 16 , 4	16 , 28 , 36	16 , 28 , 4
Δ wholesale	7 , 19 , 31	23 , 11 , 35	35 , 23 , 11	23 , 35 , 11	23 , 35 , 11	32 , 20 , 8	19 , 7 , 31	19 , 7 , 31	19 , 7 , 31	23 , 11 , 35
Δ ifo-sit.	34 , 22 , 36	34 , 29 , 11	29 , 25 , 34	29 , 4 , 35	28 , 11 , 34	10 , 4 , 16	36 , 34 , 22	34 , 22 , 29	29 , 36 , 2	28 , 22 , 29
Δ ifo-exp.	32 , 24 , 19	24 , 0 , 36	0 , 14 , 36	0 , 24 , 32	32 , 0 , 8	0 , 8 , 32	32 , 11 , 15	32 , 24 , 0	32 , 17 , 14	32 , 0 , 14
Δ zew-sit.	14 , 11 , 15	34 , 10 , 11	34 , 30 , 10	34 , 10 , 11	10 , 9 , 34	12 , 10 , 31	30 , 11 , 9	34 , 11 , 15	34 , 23 , 11	34 , 23 , 11
Δ zew-exp.	10 , 23 , 22	26 , 22 , 27	26 , 27 , 15	26 , 15 , 14	26 , 14 , 15	23 , 11 , 0	22 , 10 , 26	10 , 22 , 23	26 , 14 , 22	26 , 14 , 15
Δ almp	12 , 0 , 24	0 , 12 , 24	0 , 12 , 24	0 , 12 , 24	21 , 24 , 12	24 , 12 , 0	12 , 0 , 24	0 , 12 , 24	6 , 18 , 12	6 , 18 , 0
Δ vacancies	22 , 23 , 10	22 , 10 , 23	2 , 10 , 22	2 , 14 , 1	22 , 10 , 21	7 , 19 , 22	10 , 22 , 23	23 , 22 , 10	23 , 11 , 10	22 , 10 , 23
fmm	11 , 13 , 10	8 , 9 , 7	8 , 9 , 7	27 , 3 , 15	2 , 13 , 3	2 , 3 , 1	3 , 2 , 4	25 , 26 , 28	25 , 26 , 28	25 , 21 , 24
nmm	21 , 17 , 16	21 , 22 , 9	9 , 8 , 10	9 , 5 , 33	15 , 14 , 26	26 , 27 , 15	25 , 26 , 24	26 , 25 , 14	25 , 21 , 26	21 , 22 , 14
rss	11 , 12 , 13	8 , 7 , 6	32 , 33 , 31	7 , 8 , 6	8 , 10 , 9	8 , 7 , 9	8 , 11 , 10	8 , 11 , 9	8 , 25 , 26	36 , 21 , 25
tnn	10 , 8 , 11	33 , 32 , 34	33 , 32 , 34	33 , 32 , 34	9 , 8 , 10	9 , 8 , 10	10 , 9 , 8	10 , 9 , 19	19 , 28 , 25	33 , 34 , 32

Lead ordered by correlation (in absolute value, declining) of the indicator with the target series.

6 Forecast evaluation

6.1 Forecast construction and evaluation method

We evaluate out-of-sample forecasts at the three- and twelve-months horizon, with the end of the sampling window rolling from July 2005 to December 2010. I.e., the first three-month forecast is made for October 2005, the last twelve-month forecast predicts the labour market quantities in December 2011. In each estimation we include just a single indicator at one lead. The coefficients are estimated region by region with a GVAR model in differences (we rejected cointegration, thus the coefficients in H are restricted to zero) without leading region (we found only evidence for semi-strong cross-sectional dependence); the coefficients are then inserted in the full model (containing all regions) for forecasting. h-step ahead forecasts are received recursively by accumulating one-step ahead forecasts for the monthly differences starting at the last episode in the estimation sample, τ,

$$E\{\Delta\mathbf{Y}_{\tau+h}\} = \widehat{G}^{h}\Delta\mathbf{Y}_{\tau} + \sum_{\eta=1}^{h}\widehat{G}^{(h-\eta)}\hat{\Xi}_{\tau+\eta}, \tag{16}$$

which for log unemployment and employment levels results in forecasts

$$E\{\mathbf{Y}_{\tau+H}\} = Y_{\tau} + \sum_{h=1}^{H} E\{\Delta\mathbf{Y}_{\tau+h}\} = Y_{\tau} + \sum_{h=1}^{H}\widehat{G}^{h}\Delta\mathbf{Y}_{\tau} + \sum_{h=1}^{H}\sum_{\eta=1}^{h}\widehat{G}^{(h-\eta)}\hat{\Xi}_{\tau+\eta} \tag{17}$$

Thus, with 66 different sampling periods (with last 'observed' period τ) and 6 leads (indexed with $\ell \in \{1,\ldots,l\}$) per indicator j, we carry out 396 estimations (and predictions) per indicator. Error measures averaged over these 398 different GVAR predictions are reported separately per regional FEA division i, target variable m, indicator j and horizon $h = \{3, 12\}$ in Table 6; identical measures for comparison models without spatial interdependence are displayed in Tables 7 and 8. Whereas we have used logs in the estimation, we let the reported values refer to the forecast error of the variables in levels: i.e., $e_{m,i,\tau+h,j,\ell} = \exp(E\{y_{m,i,\tau+h}|\mathcal{I}(j,\ell)_{i,\tau}\}) - \exp(y_{m,i,\tau+h})$ denotes the h-periods ahead forecast error for variable m in region i with sample end τ which is yielded with indicator j at lead ℓ [that is, with information $\mathcal{I}(j,\ell)$]. Using this, we define the Mean Average Percentage Forecast Error (MAPFE) as

$$\text{MAPFE}_{m,i,j,h} = \frac{1}{lT}\sum_{\ell=1}^{l}\sum_{\tau=1}^{T}\frac{|e_{m,i,\tau+h,j,\ell})|}{\exp(y_{m,i,\tau+h})}. \tag{18}$$

We estimate and predict also a GVAR model without leading indicator, i.e. a model where the component Ξ_t entails only seasonal dummies and a break dummy to control for the pre-2005 period. In addition to the forecast errors referring to the GVAR forecasts, we report the MAPFEs resulting from the corresponding single-region VAR models without local average or other forms of spatial linkages. This enables us to identify the prospective information provided by the indicators and the forecast contribution achievable through considering spatial interdependence. To test the significance of differences in the performance between two indicators j_1 and j_2, we employ a panel version of the Diebold-Mariano (DM) test similar to the one presented by Bernoth/Pick (2011). However, the presented results rely on the

Mean Absolute Error rather than the Root Mean Squared Error used in their analysis. With $d_\tau = (|e_{m,i,\tau+h,j_2,\ell_2}| - |e_{m,i,\tau+h,j_1,\ell_1}|)$ as the difference between the absolute errors, the individual DM test is defined as

$$DM(\mathcal{I}[j_1,\ell_1],\mathcal{I}[j_2,\ell_2])_{i,m,h} = \frac{\frac{1}{T}\sum_{\tau=1}^{T} d_\tau}{\sqrt{\frac{2\pi}{T}\sum_{\theta=-\infty}^{\infty}(d_\tau - \bar{d})(d_{\tau+\theta} - \bar{d})}} \tag{19}$$

which will take on negative values if indicator j_2 at lead ℓ_2 yields on average smaller forecast errors than indicator j_1 at lead ℓ_1. The individual DM statistic has a standard normal limiting distribution, and so does the panel statistics as well:

$$\overline{DM}(\mathcal{I}[j_1],\mathcal{I}[j_2])_{m,h} = \frac{1}{\sqrt{Nl}}\sum_{i=1}^{N}\sum_{\ell=1}^{l} DM(\mathcal{I}[j_1,\ell_1],\mathcal{I}[j_2,\ell_2])_{i,m,h} \sim \mathcal{N}(0,1) \tag{20}$$

6.2 General forecast performance and the contribution of spatial information

We can see from Tables 6, 7 and 8 that the twelve-month forecast error is between 2.5 and 4.5 times the forecast error at three-month horizon; the average/median multiplier is between 3.5 and 4. The almost linear increase of the error's size with the horizon can be expected because of the unit root (which implies persistence of shocks), see e.g. Dickey/Bell/Miller (1986) or Lütkepohl (2005): shocks are persistent, and thus the probabilistic uncertainty accumulates. Employment forecasts have, with exception of Berlin/Brandenburg (BB), approximately equal performance across the three Tables. In BB, the VAR estimation produces significantly smaller forecast errors than the models using differences on the left hand. For unemployment, in contrast, the VAR in levels predicts in general worse than the VAR in differences and the GVAR; on the twelve months horizon, forecast errors are approximately 1-1.5 percentage points (0.01-0.015) higher throughout most regions and indicators if integration of the series is not accounted for.

In each Regional Division, the forecast errors for employment and unemployment reflect roughly the same number of persons. The ratio of the relative forecast errors (for unemployment over employment) in a Regional Division is more or less proportional to its unemployment rate. Thus, it doesn't come as a surprise that we predict unemployment with higher relative forecast errors in those regions where the unemployment rate is small: Bavaria (BY) and Baden-Wurttemberg (BW) show at the moment unemployment rates between four and five percentage points. That is, in these two regions a MAPFE of 17% regarding unemployment at the 12-months horizon corresponds to a forecast error of roughly 0.75 percentage points in the unemployment rate. However, this should be sufficient to provide a short illumination of the absolute size of the forecast errors and to allow for a proper judgement of the results; in the following, we focus on discussing the forecast accuracy across the various specifications.

In general, we find an improvement of the GVAR models compared to the corresponding VARs (estimated in both first differences and in levels with an additional lag) with regard to forecast accuracy. For unemployment forecasts at the 3-month horizon, the VAR models in

Table 6: Mean Absolute Percentage Forecast Error, GVAR (in Differences)

	Nord	BB	SAT	S	BY	BW	RPS	H	NRW	NSB
Unemployment; 3-month horizon										
none	0.0330	0.0252	0.0373	0.0355	0.0541	0.0378	0.0331	0.0308	0.0240	0.0307
dax	0.0330	0.0254	0.0371	0.0354	0.0540	0.0378	0.0332	0.0310	0.0242	0.0306
wholesale	0.0330	0.0252	0.0373	0.0355	0.0540	0.0381	0.0330	0.0309	0.0241	0.0309
ifo sit.	0.0330	0.0256	0.0377	0.0358	0.0533	0.0374	0.0332	0.0308	0.0238	0.0311
ifo exp.	0.0335	0.0254	0.0378	0.0358	0.0543	0.0377	0.0333	0.0312	0.0244	0.0316
zew sit.	0.0326	0.0251	0.0379	0.0356	0.0527	0.0366	0.0329	0.0304	0.0239	0.0312
zew exp.	0.0341	0.0259	0.0380	0.0355	0.0541	0.0380	0.0335	0.0310	0.0246	0.0316
almp	0.0290	0.0226	0.0354	0.0311	0.0471	0.0397	0.0329	0.0310	0.0256	0.0320
vacancies	0.0278	0.0223	0.0347	0.0308	0.0456	0.0368	0.0333	0.0291	0.0229	0.0319
fmm	0.0334	0.0257	0.0372	0.0351	0.0545	0.0384	0.0334	0.0311	0.0242	0.0306
nmm	0.0335	0.0250	0.0369	0.0353	0.0540	0.0379	0.0332	0.0308	0.0240	0.0310
rss	0.0329	0.0251	0.0376	0.0350	0.0542	0.0369	0.0325	0.0306	0.0241	0.0311
tnn	0.0332	0.0254	0.0378	0.0358	0.0540	0.0371	0.0332	0.0310	0.0241	0.0311
Unemployment; 12-month horizon										
none	0.0847	0.0734	0.0956	0.1007	0.1688	0.1622	0.1067	0.1045	0.0927	0.0929
dax	0.0846	0.0738	0.0955	0.1015	0.1687	0.1618	0.1065	0.1047	0.0933	0.0941
wholesale	0.0851	0.0741	0.0960	0.1013	0.1690	0.1620	0.1069	0.1046	0.0927	0.0937
ifo sit.	0.0828	0.0753	0.0948	0.0987	0.1593	0.1543	0.1032	0.1012	0.0873	0.0881
ifo exp.	0.0882	0.0760	0.0968	0.1024	0.1694	0.1579	0.1058	0.1044	0.0921	0.0954
zew sit.	0.0807	0.0770	0.0923	0.0938	0.1436	0.1399	0.0961	0.0942	0.0842	0.0850
zew exp.	0.0867	0.0765	0.0969	0.1021	0.1702	0.1620	0.1066	0.1044	0.0925	0.0938
almp	0.0908	0.0643	0.0794	0.0817	0.1863	0.1907	0.1264	0.1282	0.1127	0.1059
vacancies	0.0852	0.0625	0.0758	0.0770	0.1763	0.1805	0.1258	0.1170	0.0989	0.0866
fmm	0.0868	0.0752	0.0973	0.1018	0.1712	0.1658	0.1090	0.1078	0.0947	0.0933
nmm	0.0864	0.0700	0.0928	0.1007	0.1683	0.1613	0.1061	0.1044	0.0923	0.0918
rss	0.0825	0.0730	0.0958	0.1010	0.1659	0.1516	0.1007	0.1004	0.0908	0.0926
tnn	0.0859	0.0745	0.0952	0.0997	0.1668	0.1562	0.1055	0.1035	0.0929	0.0936
Employment; 3-month horizon										
none	0.0044	0.0061	0.0067	0.0067	0.0036	0.0031	0.0032	0.0030	0.0038	0.0042
dax	0.0044	0.0061	0.0067	0.0067	0.0036	0.0031	0.0032	0.0031	0.0038	0.0042
wholesale	0.0044	0.0060	0.0067	0.0066	0.0036	0.0031	0.0032	0.0031	0.0038	0.0042
ifo sit.	0.0044	0.0063	0.0070	0.0068	0.0036	0.0030	0.0032	0.0030	0.0036	0.0043
ifo exp.	0.0045	0.0062	0.0068	0.0068	0.0036	0.0031	0.0032	0.0031	0.0038	0.0042
zew sit.	0.0042	0.0062	0.0070	0.0069	0.0036	0.0030	0.0031	0.0029	0.0035	0.0044
zew exp.	0.0045	0.0063	0.0070	0.0068	0.0037	0.0031	0.0033	0.0031	0.0038	0.0044
almp	0.0041	0.0055	0.0068	0.0066	0.0045	0.0034	0.0039	0.0035	0.0049	0.0044
vacancies	0.0039	0.0054	0.0068	0.0063	0.0040	0.0034	0.0037	0.0037	0.0044	0.0042
fmm	0.0044	0.0061	0.0068	0.0067	0.0037	0.0031	0.0034	0.0032	0.0038	0.0043
nmm	0.0043	0.0060	0.0067	0.0067	0.0036	0.0031	0.0032	0.0031	0.0038	0.0043
rss	0.0043	0.0061	0.0068	0.0067	0.0036	0.0030	0.0031	0.0030	0.0038	0.0043
tnn	0.0044	0.0061	0.0068	0.0067	0.0036	0.0029	0.0032	0.0030	0.0038	0.0043
Employment; 12-month horizon										
none	0.0178	0.0299	0.0254	0.0266	0.0140	0.0131	0.0137	0.0121	0.0155	0.0157
dax	0.0179	0.0301	0.0254	0.0267	0.0140	0.0132	0.0138	0.0121	0.0155	0.0159
wholesale	0.0177	0.0299	0.0251	0.0264	0.0139	0.0131	0.0136	0.0120	0.0155	0.0156
ifo sit.	0.0180	0.0308	0.0256	0.0270	0.0132	0.0125	0.0128	0.0113	0.0145	0.0154
ifo exp.	0.0181	0.0305	0.0258	0.0271	0.0139	0.0130	0.0137	0.0123	0.0155	0.0161
zew sit.	0.0175	0.0303	0.0252	0.0268	0.0113	0.0111	0.0118	0.0099	0.0134	0.0152
zew exp.	0.0180	0.0304	0.0258	0.0269	0.0138	0.0131	0.0137	0.0123	0.0156	0.0159
almp	0.0189	0.0279	0.0242	0.0255	0.0188	0.0175	0.0182	0.0167	0.0344	0.0195
vacancies	0.0184	0.0271	0.0232	0.0249	0.0171	0.0169	0.0170	0.0168	0.0196	0.0190
fmm	0.0187	0.0301	0.0257	0.0268	0.0142	0.0136	0.0143	0.0125	0.0156	0.0158
nmm	0.0180	0.0293	0.0251	0.0265	0.0140	0.0131	0.0137	0.0123	0.0155	0.0155
rss	0.0179	0.0297	0.0255	0.0267	0.0136	0.0119	0.0129	0.0116	0.0154	0.0157
tnn	0.0179	0.0302	0.0257	0.0268	0.0135	0.0121	0.0135	0.0119	0.0155	0.0155

Scale: $1.0 = 100\%$.

Table 7: Mean Absolute Percentage Forecast Error, VAR (not differenced)

	Nord	BB	SAT	S	BY	BW	RPS	H	NRW	NSB
Unemployment; 3-month horizon										
none	0.0381	0.0274	0.0390	0.0367	0.0605	0.0391	0.0377	0.0336	0.0253	0.0359
dax	0.0379	0.0280	0.0387	0.0378	0.0604	0.0393	0.0376	0.0341	0.0276	0.0363
wholesale	0.0381	0.0277	0.0393	0.0371	0.0597	0.0399	0.0377	0.0342	0.0263	0.0362
ifo sit.	0.0385	0.0291	0.0386	0.0376	0.0609	0.0388	0.0383	0.0328	0.0245	0.0358
ifo exp.	0.0387	0.0276	0.0408	0.0379	0.0618	0.0398	0.0387	0.0308	0.0242	0.0368
zew sit.	0.0364	0.0278	0.0397	0.0365	0.0615	0.0387	0.0392	0.0350	0.0245	0.0371
zew exp.	0.0404	0.0290	0.0401	0.0368	0.0614	0.0400	0.0374	0.0340	0.0263	0.0360
almp	0.0288	0.0222	0.0363	0.0337	0.0475	0.0390	0.0274	0.0326	0.0259	0.0380
vacancies	0.0330	0.0244	0.0373	0.0356	0.0520	0.0420	0.0278	0.0373	0.0286	0.0403
fmm	0.0382	0.0274	0.0387	0.0364	0.0608	0.0392	0.0381	0.0341	0.0258	0.0361
nmm	0.0381	0.0273	0.0392	0.0369	0.0608	0.0394	0.0379	0.0338	0.0253	0.0360
rss	0.0383	0.0275	0.0392	0.0368	0.0607	0.0392	0.0375	0.0339	0.0254	0.0360
tnn	0.0380	0.0276	0.0392	0.0370	0.0600	0.0391	0.0377	0.0334	0.0257	0.0364
Unemployment; 12-month horizon										
none	0.1108	0.0795	0.1114	0.1146	0.1965	0.1800	0.1226	0.1047	0.0949	0.1070
dax	0.1120	0.0833	0.1094	0.1206	0.1844	0.1728	0.1234	0.1050	0.1049	0.1083
wholesale	0.1110	0.0819	0.1137	0.1175	0.1923	0.1871	0.1220	0.1082	0.0968	0.1069
ifo sit.	0.1135	0.0920	0.1130	0.1216	0.1891	0.1661	0.1201	0.0984	0.0897	0.1034
ifo exp.	0.1131	0.0816	0.1184	0.1194	0.2018	0.1852	0.1246	0.0964	0.0854	0.1114
zew sit.	0.1110	0.0823	0.1129	0.1144	0.1755	0.1609	0.1226	0.1023	0.0904	0.1104
zew exp.	0.1171	0.0885	0.1176	0.1162	0.2004	0.1851	0.1258	0.1106	0.0996	0.1014
almp	0.0695	0.0580	0.0879	0.0947	0.1804	0.1922	0.0921	0.1136	0.0943	0.1205
vacancies	0.0964	0.0871	0.1052	0.1078	0.1813	0.2115	0.0785	0.1076	0.1065	0.1381
fmm	0.1125	0.0793	0.1089	0.1114	0.1979	0.1823	0.1247	0.1071	0.0960	0.1075
nmm	0.1117	0.0785	0.1112	0.1145	0.1985	0.1804	0.1228	0.1048	0.0943	0.1070
rss	0.1107	0.0799	0.1123	0.1141	0.1956	0.1780	0.1217	0.1067	0.0954	0.1074
tnn	0.1088	0.0795	0.1117	0.1161	0.1921	0.1798	0.1228	0.1055	0.0960	0.1086
Employment; 3-month horizon										
none	0.0046	0.0047	0.0079	0.0077	0.0043	0.0035	0.0040	0.0035	0.0039	0.0050
dax	0.0046	0.0048	0.0074	0.0075	0.0049	0.0039	0.0045	0.0042	0.0038	0.0056
wholesale	0.0045	0.0048	0.0078	0.0076	0.0043	0.0035	0.0040	0.0035	0.0038	0.0049
ifo sit.	0.0047	0.0049	0.0077	0.0075	0.0048	0.0039	0.0041	0.0036	0.0042	0.0052
ifo exp.	0.0046	0.0049	0.0080	0.0077	0.0045	0.0036	0.0040	0.0030	0.0033	0.0052
zew sit.	0.0048	0.0048	0.0078	0.0078	0.0048	0.0036	0.0045	0.0042	0.0042	0.0055
zew exp.	0.0047	0.0050	0.0083	0.0078	0.0045	0.0036	0.0041	0.0035	0.0039	0.0054
almp	0.0038	0.0043	0.0071	0.0071	0.0048	0.0038	0.0044	0.0039	0.0038	0.0045
vacancies	0.0038	0.0045	0.0072	0.0069	0.0045	0.0040	0.0039	0.0041	0.0042	0.0048
fmm	0.0045	0.0047	0.0077	0.0077	0.0044	0.0035	0.0040	0.0036	0.0039	0.0051
nmm	0.0046	0.0048	0.0080	0.0077	0.0043	0.0035	0.0040	0.0036	0.0039	0.0051
rss	0.0046	0.0047	0.0079	0.0077	0.0043	0.0035	0.0040	0.0035	0.0039	0.0050
tnn	0.0044	0.0047	0.0078	0.0076	0.0043	0.0035	0.0040	0.0036	0.0040	0.0050
Employment; 12-month horizon										
none	0.0173	0.0169	0.0228	0.0224	0.0194	0.0185	0.0157	0.0137	0.0165	0.0171
dax	0.0177	0.0172	0.0218	0.0229	0.0190	0.0173	0.0155	0.0145	0.0150	0.0171
wholesale	0.0169	0.0173	0.0231	0.0227	0.0186	0.0185	0.0152	0.0134	0.0160	0.0164
ifo sit.	0.0189	0.0186	0.0229	0.0223	0.0202	0.0188	0.0161	0.0140	0.0180	0.0178
ifo exp.	0.0170	0.0171	0.0238	0.0222	0.0189	0.0181	0.0149	0.0111	0.0136	0.0170
zew sit.	0.0172	0.0179	0.0228	0.0230	0.0167	0.0162	0.0147	0.0139	0.0149	0.0177
zew exp.	0.0170	0.0184	0.0241	0.0226	0.0200	0.0185	0.0160	0.0142	0.0171	0.0180
almp	0.0123	0.0173	0.0205	0.0231	0.0207	0.0203	0.0167	0.0166	0.0151	0.0175
vacancies	0.0166	0.0176	0.0196	0.0207	0.0179	0.0194	0.0146	0.0125	0.0141	0.0196
fmm	0.0173	0.0171	0.0220	0.0220	0.0197	0.0186	0.0158	0.0141	0.0164	0.0173
nmm	0.0173	0.0171	0.0229	0.0224	0.0194	0.0186	0.0158	0.0138	0.0165	0.0172
rss	0.0173	0.0172	0.0230	0.0225	0.0193	0.0184	0.0155	0.0137	0.0165	0.0173
tnn	0.0166	0.0168	0.0228	0.0227	0.0187	0.0186	0.0155	0.0139	0.0165	0.0174

Estimated equation: $y_{i,t} = A_1 y_{i,t-1} + A_2 y_{i,t-2} + BX_{i,t} + u_{i,t}$
Scale: $1.0 = 100\%$.

Table 8: Mean Absolute Percentage Forecast Error, VAR in Differences (DVAR)

	Nord	BB	SAT	S	BY	BW	RPS	H	NRW	NSB
					Unemployment; 3-month horizon					
none	0.0329	0.0257	0.0364	0.0345	0.0563	0.0375	0.0347	0.0325	0.0246	0.0335
dax	0.0328	0.0259	0.0363	0.0345	0.0563	0.0374	0.0348	0.0325	0.0247	0.0332
wholesale	0.0329	0.0257	0.0364	0.0346	0.0563	0.0378	0.0347	0.0326	0.0246	0.0336
ifo sit.	0.0329	0.0261	0.0368	0.0348	0.0560	0.0372	0.0346	0.0323	0.0244	0.0337
ifo exp.	0.0334	0.0261	0.0370	0.0349	0.0568	0.0375	0.0351	0.0330	0.0251	0.0344
zew sit.	0.0327	0.0257	0.0371	0.0344	0.0553	0.0363	0.0341	0.0318	0.0244	0.0337
zew exp.	0.0340	0.0264	0.0372	0.0346	0.0564	0.0377	0.0352	0.0327	0.0249	0.0344
almp	0.0291	0.0227	0.0335	0.0306	0.0520	0.0390	0.0329	0.0349	0.0284	0.0360
vacancies	0.0276	0.0220	0.0331	0.0305	0.0503	0.0364	0.0322	0.0331	0.0252	0.0360
fmm	0.0333	0.0260	0.0363	0.0343	0.0567	0.0381	0.0349	0.0328	0.0248	0.0329
nmm	0.0333	0.0254	0.0358	0.0343	0.0562	0.0376	0.0348	0.0324	0.0248	0.0336
rss	0.0328	0.0256	0.0368	0.0344	0.0565	0.0365	0.0338	0.0324	0.0247	0.0339
tnn	0.0331	0.0259	0.0370	0.0347	0.0563	0.0368	0.0349	0.0326	0.0247	0.0336
					Unemployment; 12-month horizon					
none	0.0842	0.0734	0.0964	0.1005	0.1718	0.1618	0.1089	0.1063	0.0948	0.0974
dax	0.0843	0.0741	0.0961	0.1011	0.1712	0.1616	0.1085	0.1063	0.0954	0.0984
wholesale	0.0846	0.0740	0.0969	0.1013	0.1720	0.1616	0.1092	0.1067	0.0948	0.0983
ifo sit.	0.0822	0.0751	0.0953	0.0979	0.1639	0.1558	0.1039	0.1026	0.0891	0.0932
ifo exp.	0.0874	0.0762	0.0977	0.1021	0.1735	0.1569	0.1085	0.1066	0.0938	0.1001
zew sit.	0.0802	0.0763	0.0926	0.0924	0.1488	0.1405	0.0983	0.0956	0.0873	0.0894
zew exp.	0.0859	0.0762	0.0976	0.1019	0.1738	0.1615	0.1091	0.1059	0.0946	0.0985
almp	0.0845	0.0655	0.0818	0.0829	0.1946	0.1914	0.1253	0.1298	0.1163	0.1173
vacancies	0.0805	0.0618	0.0783	0.0788	0.1828	0.1822	0.1181	0.1229	0.1015	0.0999
fmm	0.0861	0.0750	0.0979	0.1022	0.1740	0.1655	0.1108	0.1092	0.0976	0.0968
nmm	0.0846	0.0698	0.0932	0.1000	0.1714	0.1607	0.1087	0.1061	0.0953	0.0962
rss	0.0820	0.0729	0.0970	0.1004	0.1694	0.1504	0.1019	0.1027	0.0949	0.0977
tnn	0.0852	0.0744	0.0954	0.0997	0.1702	0.1549	0.1088	0.1055	0.0957	0.0980
					Employment; 3-month horizon					
none	0.0043	0.0061	0.0071	0.0073	0.0038	0.0031	0.0041	0.0034	0.0039	0.0048
dax	0.0044	0.0062	0.0070	0.0073	0.0038	0.0031	0.0041	0.0035	0.0039	0.0048
wholesale	0.0044	0.0061	0.0070	0.0073	0.0038	0.0031	0.0041	0.0034	0.0039	0.0048
ifo sit.	0.0044	0.0064	0.0072	0.0074	0.0038	0.0030	0.0038	0.0033	0.0037	0.0048
ifo exp.	0.0045	0.0063	0.0072	0.0074	0.0038	0.0031	0.0041	0.0035	0.0039	0.0049
zew sit.	0.0043	0.0063	0.0073	0.0075	0.0037	0.0029	0.0038	0.0032	0.0036	0.0050
zew exp.	0.0045	0.0063	0.0073	0.0074	0.0039	0.0031	0.0042	0.0035	0.0039	0.0050
almp	0.0041	0.0054	0.0072	0.0072	0.0045	0.0033	0.0049	0.0045	0.0049	0.0051
vacancies	0.0041	0.0053	0.0071	0.0068	0.0041	0.0033	0.0047	0.0045	0.0045	0.0049
fmm	0.0044	0.0062	0.0071	0.0074	0.0039	0.0031	0.0042	0.0035	0.0039	0.0049
nmm	0.0043	0.0060	0.0070	0.0073	0.0038	0.0030	0.0041	0.0035	0.0039	0.0049
rss	0.0043	0.0062	0.0071	0.0074	0.0038	0.0030	0.0039	0.0034	0.0039	0.0049
tnn	0.0044	0.0062	0.0071	0.0074	0.0038	0.0029	0.0041	0.0034	0.0039	0.0049
					Employment; 12-month horizon					
none	0.0178	0.0300	0.0257	0.0274	0.0143	0.0133	0.0147	0.0127	0.0158	0.0165
dax	0.0179	0.0302	0.0257	0.0276	0.0143	0.0135	0.0146	0.0126	0.0157	0.0167
wholesale	0.0178	0.0299	0.0254	0.0272	0.0143	0.0133	0.0147	0.0126	0.0158	0.0164
ifo sit.	0.0182	0.0308	0.0259	0.0278	0.0137	0.0128	0.0136	0.0117	0.0147	0.0164
ifo exp.	0.0181	0.0305	0.0262	0.0279	0.0144	0.0132	0.0149	0.0130	0.0157	0.0171
zew sit.	0.0177	0.0304	0.0255	0.0275	0.0120	0.0113	0.0129	0.0102	0.0137	0.0160
zew exp.	0.0181	0.0305	0.0261	0.0277	0.0143	0.0133	0.0147	0.0128	0.0159	0.0168
almp	0.0183	0.0279	0.0250	0.0261	0.0190	0.0171	0.0188	0.0175	0.0213	0.0210
vacancies	0.0181	0.0265	0.0242	0.0260	0.0174	0.0166	0.0184	0.0180	0.0199	0.0202
fmm	0.0187	0.0303	0.0260	0.0275	0.0145	0.0138	0.0152	0.0129	0.0159	0.0166
nmm	0.0178	0.0293	0.0254	0.0275	0.0143	0.0133	0.0148	0.0128	0.0158	0.0163
rss	0.0179	0.0299	0.0258	0.0276	0.0140	0.0120	0.0139	0.0122	0.0158	0.0166
tnn	0.0179	0.0303	0.0259	0.0277	0.0140	0.0123	0.0147	0.0125	0.0158	0.0162

Estimated equation: $\Delta y_{i,t} = A\Delta y_{i,t-1} + BX_{i,t} + u_{i,t}$
This equation is theoretically equivalent to that used for Table 7 if $-(I - A_1 - A_2) \sim 0$ and $A = -A_2$.
Scale: $1.0 = 100\%$.

levels (Table 7) show smaller MAPFEs than the corresponding GVARs only in six indicator-region combinations (out of 130 tabulated). Here, the average of ratio of the GVAR-related over the VAR-related MAPFE, $\frac{1}{NJ}\sum_{i=1}^{N}\sum_{j\epsilon J}\frac{MAPFE_{GVAR,i,j}}{MAPFE_{VAR,i,j}}$, mounts to 0.914. At the one-year horizon, we find an improvement in the forecast accuracy in 108 of 130 GVAR vs. VAR comparisons. The ratio is on average 0.891; this number means that the forecast error in the unemployment forecasts is reduced on average by roughly ten percent. We find a similar pattern in the short-run employment forecasts where the average GVAR-VAR MAPFE ratio is 0.911, and where we find smaller relative forecast errors for the GVAR in 102 of 130 region-indicator combinations. At the twelve-month horizon we find more accurate forecasts for the GVAR only in 71 of the 130 comparisons, and the GVAR-VAR forecast error ratio exceeds one.

Amongst the employment forecasts at the three-month horizon, the RD of Berlin/Brandenburg (BB) is somewhat outstanding insofar that for each indicator the GVAR is outperformed by the VAR in levels. Here, spatial interdependence seems to bear not only irrelevant but misleading information with regard to employment. This mis-information amplifies over time and affects also the other (partially) Eastern German regions: in BB, the relative loss in accuracy (mounting to 1.708) is at the 12-month horizon two to three times as high as the relative loss at the 3-month horizon (an average ratio of 1.279), and in the RDs Nord, Saxony (S) and Saxony-Anhalt/Thuringia (SAT) the ratios mount at the 12-months horizon to 1.028, 1.079 and 1.026, respectively. That is, we find the GVAR to perform on average neither better nor worse than the level VAR when forecasting employment one year ahead; in the other three scenarios, the improvement of the GVAR is (even statistically) significant.

Forecast accuracy is more similar between the GVAR and the DVAR in Table 8; the amount of the improvement in forecast accuracy is obviously smaller. The average MAPFE-ratios mount to 0.979 for unemployment at the three-month horizon, to 0.987 in the predictions for unemployment one-year ahead, to 0.935 for three-months ahead employment forecasts and to 0.978 for employment at the twelve-month horizon. When we count the pairwise comparisons where the GVAR performs better than the DVAR, we find with regard to unemployment forecasts, that the (non-spatial) DVAR yield smaller forecast errors at the three-month horizon in 52 pairwise comparisons and larger errors in 77 comparisons. At the twelve-month horizon, DVARs have a better performance in 41 and a worse in 86 comparisons. The spatial GVAR models tend to predict unemployment more accurate than the DVAR in Western Germany with the exception of Baden-Wurttemberg), and less accurate in Eastern Germany. In forecasting employment, however, the GVAR outperforms the DVAR (again with the exception of Baden-Wurttemberg at the three-month horizon). All in all, accounting for spatial co-development seems to provide some information which can be used for prediction.

6.3 Forecast comparison across the indicators

Since we have found evidence for slightly more accurate forecasts of the GVAR model so far, we will focus on these when comparing the forecast content of the indicators. Across all forecasts for which DM panel tests are reported in Table 9, a number of trends may be recognized. First, the variation of the forecast errors between the different indicators is

Table 9: Cross-Indicator Comparison: Panel Diebold-Mariano Tests

Tested	Smaller MAE than Model ...					
Indicator	without Indicator		with Precipitation (rss)		with ZEW situation.	
	U	L	U	L	U	L
			3 month horizon			
dax	-4.152***	-3.904***	-2.260**	-3.147***	0.903	0.060
wholesale	-1.293	0.039	-1.267	-1.702*	1.671*	1.099
ifo sit.	-1.956*	-0.573	-2.736***	-2.255**	-0.831	0.435
ifo exp.	-4.509***	-5.685***	-5.274***	-5.694***	-1.169	-1.460
zew sit.	-2.068**	-1.323	-2.372**	-2.094**	—	—
zew exp.	-3.802***	-6.892***	-5.266***	-7.465***	-1.462	-2.498**
almp	5.127***	-4.667***	4.422***	-4.863***	4.566***	-2.746***
vacancies	7.559***	-1.144	6.396***	-1.443	7.432***	-0.347
fmm	-0.391	-6.629***	-1.709*	-5.653***	0.890	-1.206
nmm	-1.237	-1.789*	-2.527**	-2.445**	0.475	0.273
rss	1.061	1.227	—	—	2.372**	2.094**
tnn	-1.095	-0.604	-1.872*	-1.147	0.837	1.741*
			12 month horizon			
dax	-2.186**	-2.961***	-8.051***	-7.883***	-7.226***	-6.992***
wholesale	-4.614***	5.124***	-10.708***	-5.853***	-8.204***	-5.884***
ifo sit.	4.212***	2.301**	-1.235	-1.719*	-5.865***	-6.159***
ifo exp.	-1.593	-4.006***	-7.762***	-9.963***	-7.632***	-7.346***
zew sit.	7.332***	6.250***	3.384***	3.481***	—	—
zew exp.	1.222	-0.607	-6.737***	-7.213***	-6.196***	-6.697***
almp	-3.979***	-11.084***	-5.037***	-11.627***	-8.369***	-12.185***
vacancies	-1.110	-8.562***	-2.245**	-9.478***	-5.646***	-10.818***
fmm	-5.212***	-7.033***	-9.761***	-9.425***	-8.399***	-6.984***
nmm	2.155**	-1.276	-4.981***	-6.140***	-5.976***	-5.895***
rss	9.460***	8.915***	—	—	-3.384***	-3.481***
tnn	1.262	2.740***	-5.314***	-3.730***	-6.284***	-5.214***

*/**/***: Significant at the 10%/ 5% /1% confidence level

rather small. It is hardly possible to identify a clearly superior leading indicator, albeit we have to admit that our analysis might be somewhat ‘conservative’ against them: the DM test does not account for the nested structure and is thus in favor of the more parsimonious model without indicator (see Clark/West, 2007). At the very short run, no indicator seems significantly superior to the model without indicators with regard to forecasts for the two target variables at the same time. Precipitation yields on average smaller forecast errors in predicting both employment and unemployment; the differences to the forecasts without indicator are however not significant. Vacancies and ALMP can contribute significantly to the forecast accuracy of unemployment, albeit at the cost of (for ALMP even significantly) less accurate employment forecasts. Surprisingly, business cycle indicators improve neither unemployment nor employment forecasts at the three-months horizon.

On the one-year horizon the picture changes. Labour market related indicators now lead in general to worse forecasts. Judgements on the current economic situation, in contrast, improve the forecast accuracy relative to forecasts without indicator significantly for both target variables; other business cycle indicators (even the expectations collected together with the judgements on the current situation) don’t show a similar potential with regard to labour market forecasts. However, the highest score of a DM panel test against the model without indicator is again achieved by those forecasts using precipitation as an indicator. To strengthen the evidence of the two best-performing indicators, precipitation and the ZEW economic situation index, we test forecasts of all other indicators against these. As the third to sixth column in Table 9 show, forecasts employing either precipitation or ZEW situation are more accurate than any other. However, when comparing the two against each other, we find precipitation outperformed by the business-cycle indicator.

6.4 Development of forecast errors over time

To complete the analysis of the forecast errors, we present and discuss their development over time. To demonstrate a pattern that seems to us generalizable, we show only a figure for forecasts regarding unemployment at the twelve-month horizon in a single region for a small selection of indicators. We choose the regional division Baden-Wurttemberg (BW) since here the forecast errors are relatively high and differences between the models are more pronounced. Similar graphs for unemployment and employment forecasts at the three- and twelve-month horizon across all regions are provided in Appendix B. The figures include forecasts without indicator, with vacancies (one candidate for the best short-run indicator), ZEW situation (best long-run indicator) and precipitation (relatively good performance in both long and short run). For these, we include additionally to the GVAR forecasts even the VAR predictions.

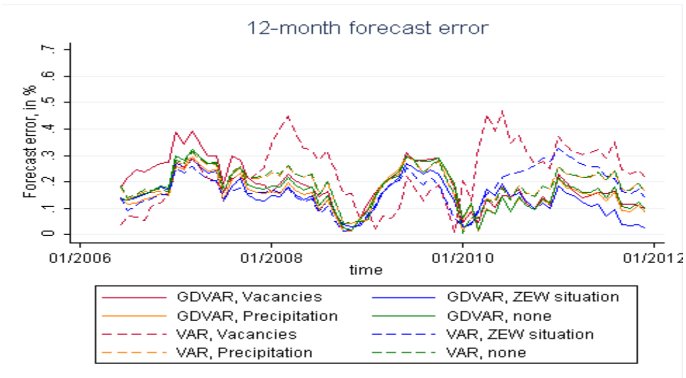

Figure 1: Development of forecast accuracy : Unemployment, h=12, Baden-Wurttemberg

Fig. 1 shows (alike most Graphs in Appendix B) that the Absolute Percentage Forecast Errors at the same point in time are highly correlated across the various forecasting models. Forecast errors in the 12-month ahead unemployment predictions are in general high at the beginning of our evaluation period; they decline to a first minimum of forecast's inaccuracy in the predictions made for late 2008 and early 2009, increased again to a peak for the second half-year of 2009, declined afterwards etc. This pattern holds for most forecast regardless of the indicator employed, and for most regions. That is, the accuracy of forecasts seems to be affected to a large extent by shocks or innovations which are not accounted for in the models.

We can see as well that the order of the different forecasting models changes over time. According to Fig. 1, the GVAR forecast relying on ZEW situation achieved the smallest error of the displayed forecasts approximately from Fall 2007 to Summer 2008, and from late 2010 till the end of 2011. In the time between, we find periods where the (non-spatial) VAR with ZEW situation as indicator, the VAR including vacancies or the GVARs with precipitation and without indicator performed best. This suggests that findings on the comparative performance of indicators are quite sensitive with regard to the period used for evaluation. Furthermore, the figure present the forecast improvement of precipitation in the proper light. An eye-glass is needed to distinguish between the precipitation forecasts and those without indicator; the further line is most often extremely close to the latter. That is, despite its statistical significance, the forecast improvement of precipitation (and supposedly the other climate indicators) is quantitatively marginal. Finally, we can observe that VAR forecasts employing indicators often show a good performance over a certain time span (e.g. vacancies in 2009) but extremely inaccurate forecasts in other periods (vacancies in early 2008 and in 2010). In contrast, the GVAR forecasts rarely reach this good performance but even less are far off. Thus, the main advantage of the GVAR forecasts seems to be in their reduced sensitivity with regard to the indicators.

7 Conclusion

The focus of this paper is on forecasting regional labour markets. It is broadly accepted that two aspects regarding the modeling strategy are essential for the accuracy of forecast: a parsimonious model focusing on the important structures, and the quality of prospective information. Thus, our aim is twofold. First, we establish a Global VAR framework, a technique that considers spatio-temporal dynamics in a multivariate setting, that allows for spatially heterogeneous slope coefficients, and that is nevertheless feasible for data without extremely long time dimension. Second, we use this framework to analyse the prospective information regarding the economy due to spatial co-development of regional labour markets in Germany. We employ the same model to examine the information content of a set of commonly used business-cycle indicators, and compare it with the predictive information provided by labour-market immanent indicators and climate variables.

The GVAR model has the advantage of allowing for both cross-sectionally strong (factor) and weak (spatial) dependence. Through estimation of the exponent of divergence we can distinguish between the two from inside the modeling framework. We find in the data support for semi-strong cross-sectional dependence which seems reasonable since Germany is a polycentric economy, in contrast to the UK or continental France where clearly dominant spatial units exist. Because of the less-than-strong interregional dependence, it is sufficient to account for the joint influence of the other regions by constructing spatially weighted aggregates. These local averages are considered to be weakly exogenous. As a second specification issue we investigate the existence of common nonstationary trends. However, nonstationary idiosyncratic components forestall cointegration. Thus, our basic GVAR specification is a model in first differences without imposing cointegration relations and without including a dominant region.

In our forecasting experiment we estimate this basic specification as well as GVAR models which are augmented by leading indicators and use them to predict unemployment and employment in the FEA Regional Divisions three-months and twelve-months ahead. For comparison we forecast for each indicator even a VAR in differences (the same model as the GVAR without local averages) and a VAR in levels (with lag order increased by one). The forecasting experiment starts with data until June 2005, the sample expands month-by-month until December 2010. The forecast accuracy is evaluated by comparing Mean Absolute Percentage Forecast Errors and panel Diebold-Mariano tests.

We can indeed assess a systematic improvement in the forecast accuracy due to accounting for spatial interdependence. The degree of improvement depends on the target variable and the horizon but is robust across all indicators. Albeit, there exist for any horizon regions where all GVAR forecasts for one of the two target variables are less accurate than the corresponding non-spatial forecasts, regardless of the indicator. The indicators themselves are evaluated only by comparison amongst the GVAR-based forecasts. At the three-month horizon, vacancies are the only indicator with significant forecast content regarding one target variable (unemployment) that does not come at a significant cost in forecasting the second target variable, compared to forecasts without indicator. At the twelve-month horizon, forecasts on both target variable can be improved significantly (relative to forecasts without indicators) by judgements on the current economic situation collected in the ZEW and the ifo business-tendency surveys. However, the simulated out-of-sample forecasts assess a similarly high forecast content to Precipitation. The latter produces on average significantly more accurate regional labour-market forecasts than the ifo business situation index, and is only outperformed by ZEW economic situation. Thus, even the best performing indicators seem to provide at the moment only limited prospective information.

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A Exponent of divergence – simulation

```
% function factor_exponent()
% Program version: GNU Octave 3.2.4 -- filename: factor_exponent.m
function [epsilon s_epsilon Lambdaval] = factor_exponent(Y,reps)
   [T N] = size(Y);
   Llength = (N-2) * reps;
   Lambdaval = zeros(Llength,2);
   row = 0;
   z1 = [1:1:N]';
   for n = 2:N-1
      for rep = 1:reps
          row = row + 1 ;
          z2 = unifrnd(0,1,N,1); z = [z1  z2]; z = sortrows(z,2);
          idselect = z(1:n,1);
          X = Y(:,idselect);
          S = cor(X,X);
          if n < 7
             lambda = eig(full(S));
          elseif n > 6
             lambda  = eigs(S,1) ;
          end;
          Lambdaval(row,1) = log(abs(lambda(1,1)));
          Lambdaval(row,2) = log(n);
       end;
   end;
   % use correlation rather than covariance
   S = cor(Y,Y);
   lambda = eigs(S,1);
   for rep = 1:reps
       row = row + 1 ;
       Lambdaval(row,1) = log(abs(lambda(1,1)));
       Lambdaval(row,2) = log(N);
   end;
   y = (Lambdaval(:,1)) - (Lambdaval(:,2));
   x1 = ones(length(Lambdaval),1); x2 = (Lambdaval(:,2)); x = [x1 x2];
   [b_ols , s_ols , r_ols] = ols(y,x);
   s_bols = (x'*x)\eye(length(b_ols)) * s_ols;
   epsilon = b_ols(2,1); s_epsilon = s_bols(2,2);
end;
```

Table 10: Simulated critical values for the exponent of divergence ($-\epsilon$)

Model	T	N	mean	5%	10%	90%	95%
nofactor	10	100	-0.4671	-0.5582	-0.5416	-0.3853	-0.3596
nofactor	20	100	-0.4360	-0.4945	-0.4821	-0.3873	-0.3736
nofactor	50	100	-0.5085	-0.5389	-0.5326	-0.4838	-0.4758
nofactor	100	100	-0.5145	-0.5351	-0.5309	-0.4963	-0.4899
nofactor	10	200	-0.6176	-0.6898	-0.6741	-0.5622	-0.5423
nofactor	20	200	-0.5915	-0.6346	-0.6261	-0.5567	-0.5465
nofactor	50	200	-0.6344	-0.6561	-0.6528	-0.6159	-0.6092
nofactor	100	200	-0.6287	-0.6447	-0.6409	-0.6156	-0.6120
weakfactor	10	100	-0.1535	-0.4698	-0.4246	0.1223	0.1943
weakfactor	20	100	-0.0590	-0.3209	-0.2716	0.1508	0.2256
weakfactor	50	100	-0.1092	-0.2588	-0.2227	0.0007	0.0234
weakfactor	100	100	-0.1089	-0.1916	-0.1719	-0.0470	-0.0282
weakfactor	10	200	-0.2213	-0.5851	-0.5163	0.0503	0.1205
weakfactor	20	200	-0.1312	-0.4151	-0.3463	0.0705	0.1176
weakfactor	50	200	-0.1374	-0.2813	-0.2400	-0.0406	-0.0201
weakfactor	100	200	-0.1223	-0.1971	-0.1809	-0.0687	-0.0557
strongfactor	10	100	0.1601	-0.1563	-0.0883	0.3937	0.4648
strongfactor	20	100	0.2477	0.0235	0.0745	0.4203	0.4583
strongfactor	50	100	0.0921	-0.0099	0.0118	0.1663	0.1892
strongfactor	100	100	0.0289	-0.0345	-0.0181	0.0724	0.0868
strongfactor	10	200	0.1302	-0.2058	-0.1170	0.3690	0.4166
strongfactor	20	200	0.1958	-0.0089	0.0423	0.3425	0.3829
strongfactor	50	200	0.0639	-0.0253	-0.0042	0.1301	0.1486
strongfactor	100	200	0.0155	-0.0318	-0.0210	0.0524	0.0640

B Figures: Development of forecast accuracy

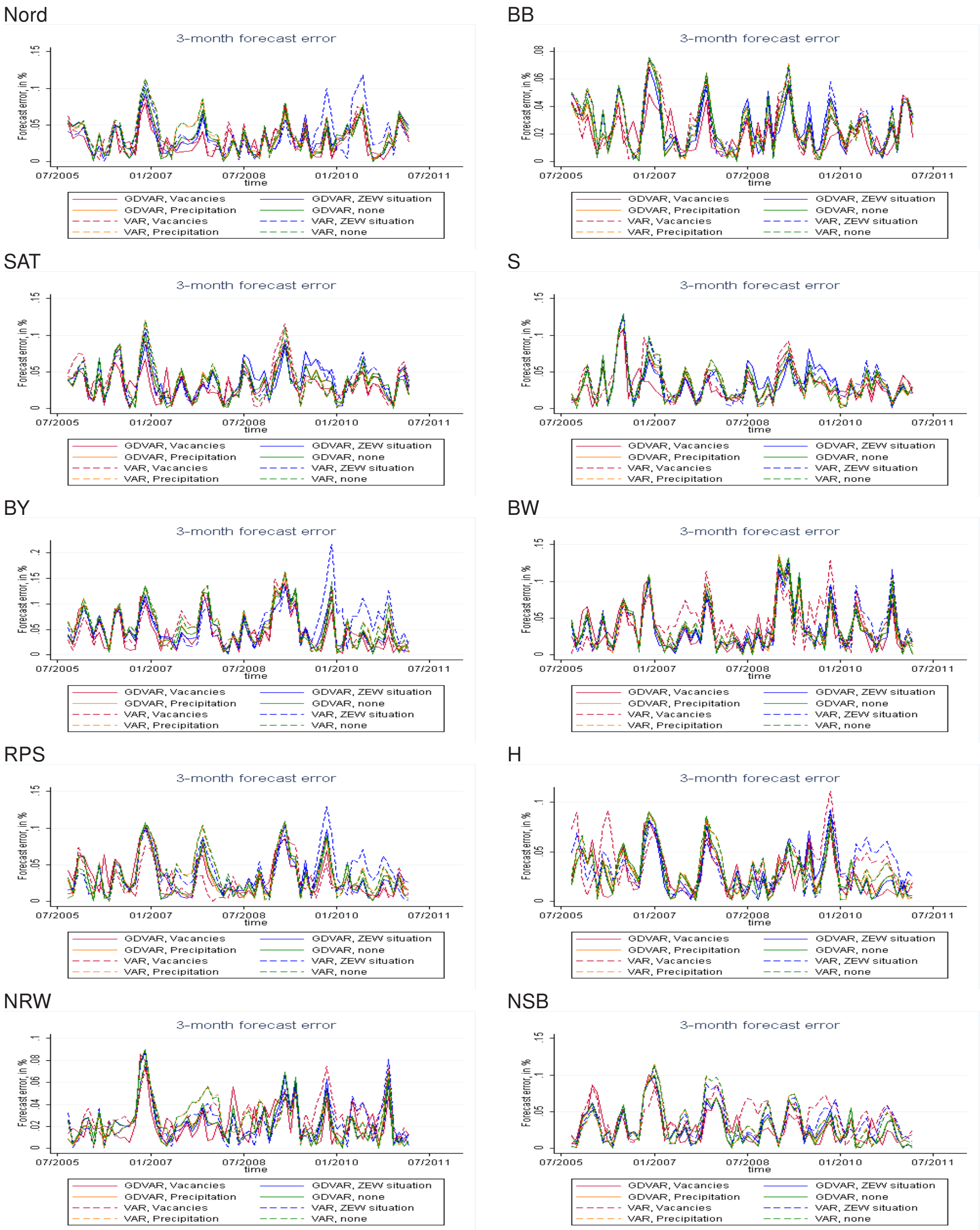

Figure 2: Relative forecast errors over time: Unemployment, $h = 3$

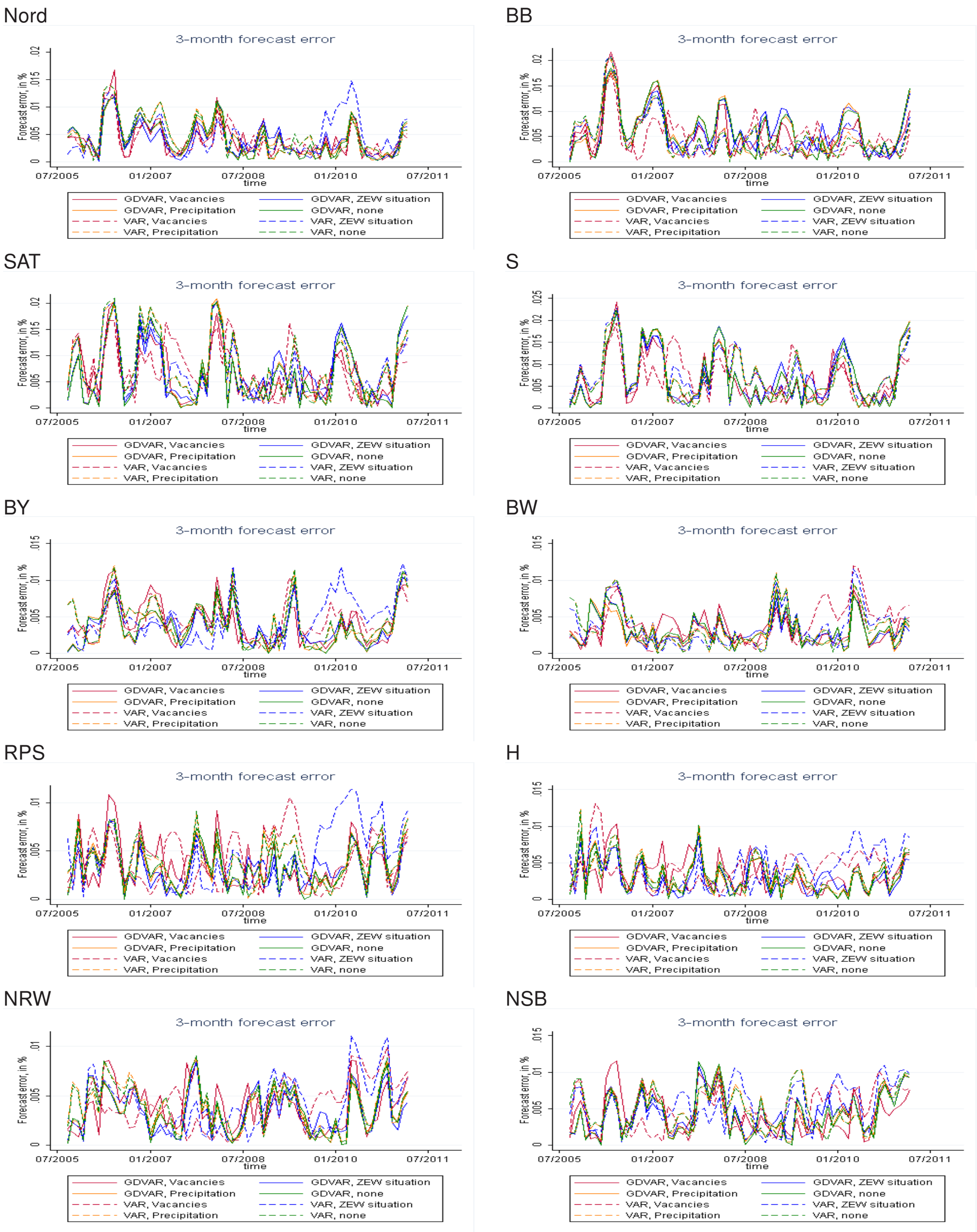

Figure 3: Relative forecast errors over time: Employment, $h = 3$

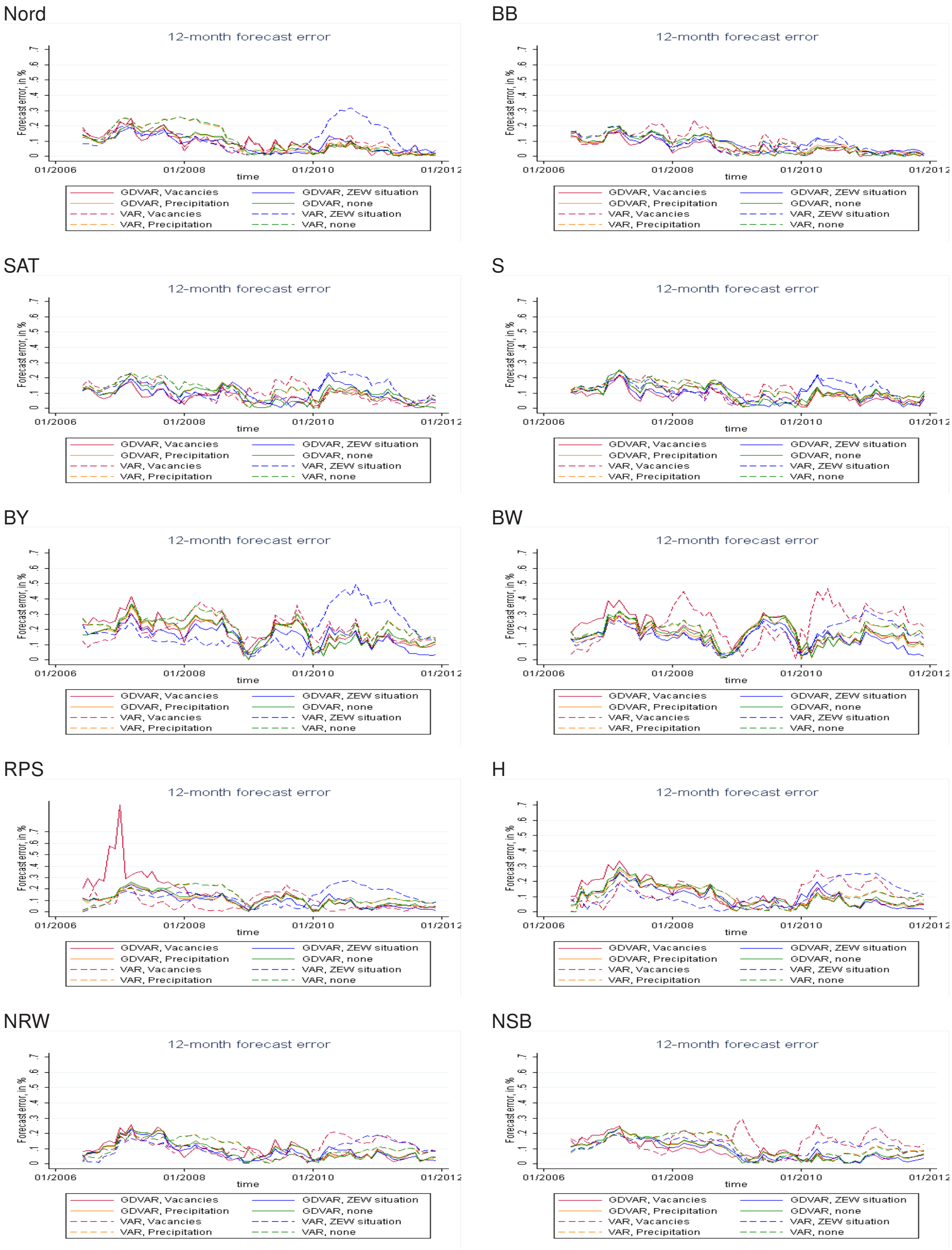

Figure 4: Relative forecast errors over time: Unemployment, $h = 12$

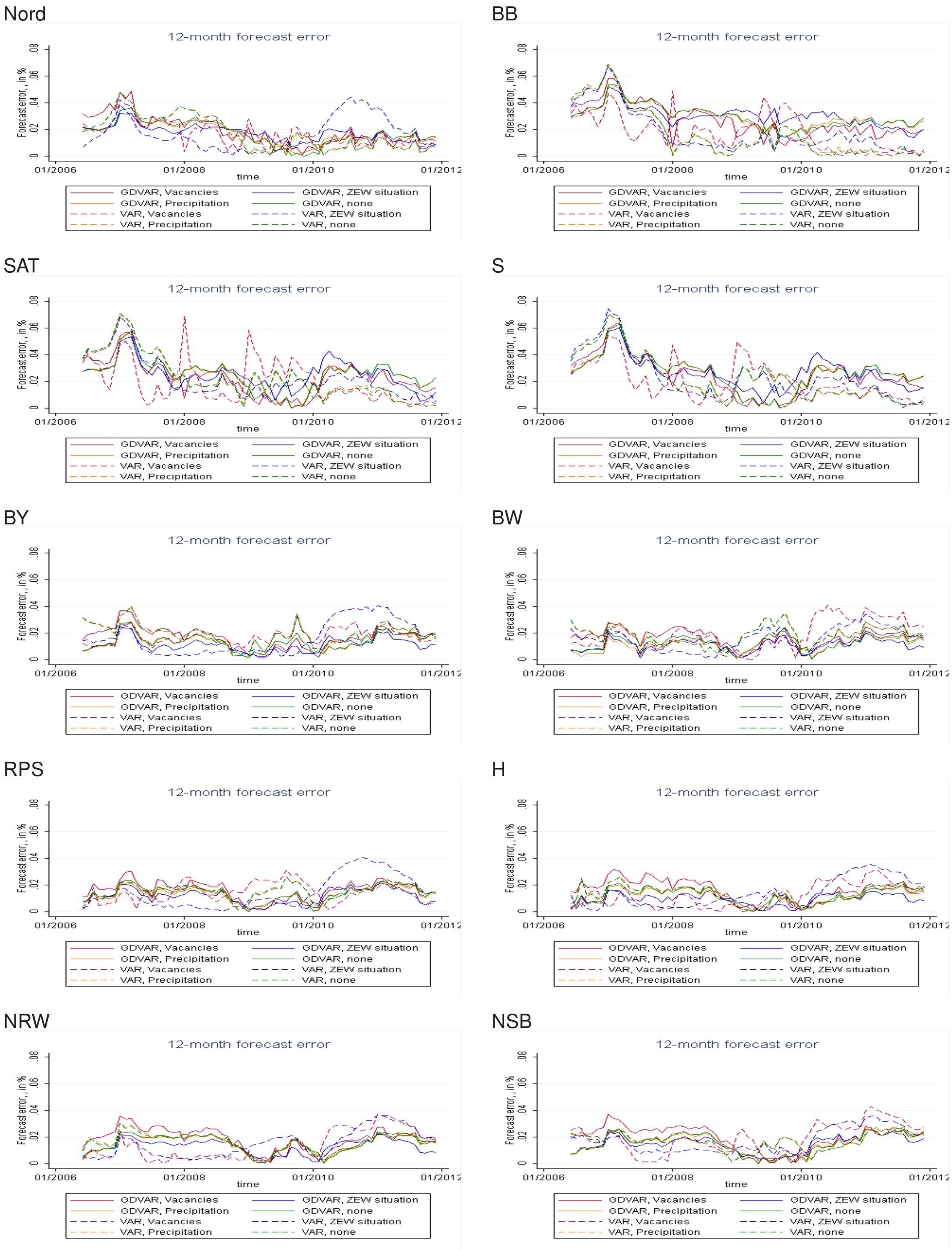

Figure 5: Relative forecast errors over time: Employment, $h = 12$

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