Estimating Regional Business Cycles for Germany Based on Unemployment Data

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Abstract

This paper attempts to find regional differences in the business cycle for German regions. The region-specific cycles are estimated using a latent dynamic factor model, where unemployment figures serve as a proxy for the business cycle on the county level, or NUTS-3 level. Applying the Weighted Orthogonal Procrustes (WOP) approach to estimate the model, I first discuss several model selection criteria and determine an appropriate model specification that is used in the estimation. In the second step, I use a new approach to determine the sparsity structure of the loadings matrix and estimate a sparse dynamic factor model. Both models reveal substantial regional differences and indicate that the labor market is driven by at least three distinct cycles.

Keywords: Bayesian estimation; factor model; Weighted Orthogonal Procrustes; sparse loadings structure

1 Introduction

Investigation of the common movements in business cycles across different countries, or different regions within the same country, has found much research interest over the past years. The major questions revolve around the identification and estimation of these common business cycles, whether they are converging or decoupling, and what lies behind the regional differences. [1], for instance, analyze the synchronization of employment expansion and contraction phases for 58 large U.S. cities by means of a Markov-switching model, and [2] use a clustering approach to determine which states in the U.S. share a common pattern with respect to the characteristics of their business cycles, using employment data as a proxy for the regional business cycle. Other authors focus directly on employment, e.g. in the seminal paper by [3]. I estimate a latent dynamic factor model for monthly unemployment in the 402 counties in Germany, attempting to find common movements and distinct patterns and the relation to the business cycle.

2 Methodology

Lately, latent factor models have played an important role in the analysis of business cycles and their region-specific differences, see e.g. [4], who use a Gibbs sampling approach, which has been applied by many researches since then.

To obtain estimates for the model parameters, I use the multi-move Gibbs sampler from [5], but leaving the rotation problem unsolved. The factors are obtained by forward-filtering backward-sampling, using a square-root Kalman filter described in [6]. Afterwards, the Gibbs output is postprocessed by the Weighted Orthogonal Procrustes (WOP) approach from [7]. Next, I discuss several model selection criteria applied to static factor models by [8]. Aside from the Akaike Information Criterion (AIC), two versions of the Bayesian Information Criterion (BIC) and the ICOMP criterion, I consider the Deviance Information Criterion (DIC) by [9] and the marginal likelihood, which is calculated using Chib's method, see [10]. Eventually, I apply the approach from [11] to find a sparse loadings structure and estimate the factor model with this sparse loadings structure.

3 Empirical Results

The data contains 82 monthly observations of absolute unemployment for 402 German counties. X-12 ARIMA is used to remove the seasonal pattern and the absolute numbers are transformed into growth rates. The model selection criteria find up to seven factors, but all agree on the lag orders in the factors and errors, which are both 0. Based on residual diagnostics, which confirm the lag order 0 for the errors, and the distribution of the Bayes factors, however, I choose lag order 1 for the factors. Scaling and orthogonally transforming the factors, which is admissible under the chosen sampling approach, results in factors that closely resemble the first seven principal components, with the correlation exceeding 0.995 for the first three factors and exceeding 0.96 for the remaining four.

As the posterior estimates can be arbitrarily orthogonally transformed, I rotate the factors and loadings such that the first is maximally aligned with the ifo business climate indicator, obtaining a correlation coefficient of -0.8503. The remaining factors are rotated such that their kurtosis is maximized, hoping to find unique shocks that hit only particular regions. Out of 40.89% of the variation explained by the factors, the business cycle factor and an additional general factor account for almost 30%. The remaining factors are hard to interpret.

Thus, I next identify the sparse structure directly from the Gibbs output transformed by WOP, using the approach from [11]. This yields a degree of sparsity of 0.7935 and produces three region-specific factors, see Figure 1, the first of which has a correlation with the ifo business climate indicator of -0.6687. This factor has the highest loadings in economically thriving regions again, see Figure 2. The second and third factors are clearly region-specific, while the fourth factor has nonzero loadings in regions particularly exposed to seasonal unemployment. The remaining three factors have only very few nonzero loadings and lack a clear interpretation. As a wider HPDI is chosen, two of the remaining factors vanish.

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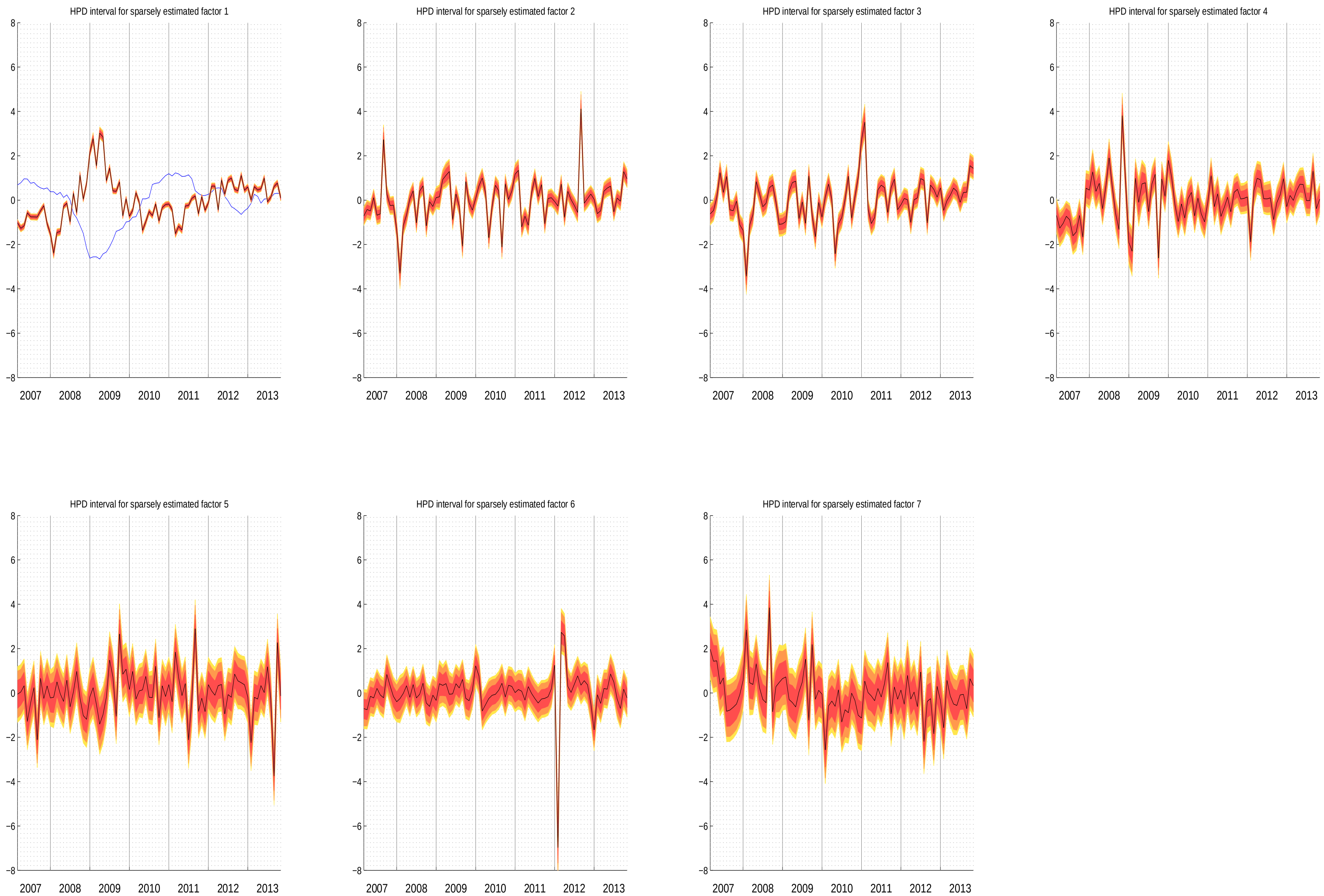

Figure 1: Factors and their highest posterior density (HPD) intervals. Black lines are the median, red patches denote 68% HPDI, orange patches denote 90% HPDI, and yellow patches denote 95% HPDI. The blue line in the first panel is the ifo business climate indicator.

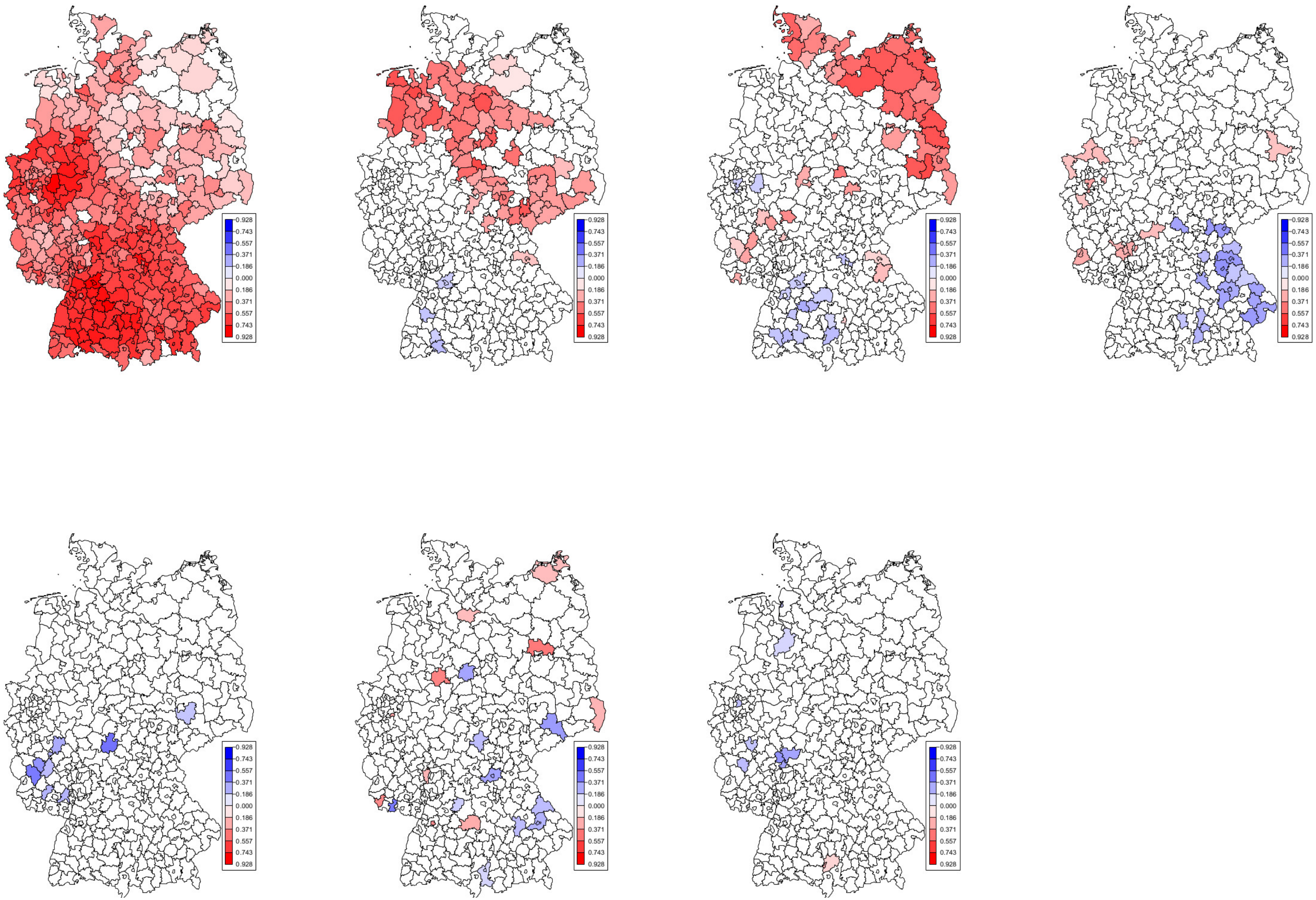

Figure 2: Loadings patterns per factor for the sparse factor model.

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