Persistent Disparities in Regional Unemployment: Application of a Spatial Filtering Approach to Local Labour Markets in Germany

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ABSTRACT

The geographical distribution and persistence of regional/local unemployment rates in heterogeneous economies (such as Germany) have been, in recent years, the subject of various theoretical and empirical studies. Several researchers have shown an interest in analysing the dynamic adjustment processes of unemployment and the average degree of dependence of the current unemployment rates or gross domestic product from the ones observed in the past. In this paper, we present a new econometric approach to the study of regional unemployment persistence, in order to account for spatial heterogeneity and/or spatial autocorrelation in both the levels and the dynamics of unemployment. First, we propose an econometric procedure suggesting the use of spatial filtering techniques as a substitute for fixed effects in a panel estimation framework. The spatial filter computed here is a proxy for spatially distributed region-specific information (e.g., the endowment of natural resources, or the size of the 'home market') that is usually incorporated in the fixed effects coefficients. The advantages of our proposed procedure are that the spatial filter, by incorporating region-specific information that generates spatial autocorrelation, frees up degrees of freedom, simultaneously corrects for time-stable spatial autocorrelation in the residuals, and provides insights about the spatial patterns in regional adjustment processes. In the paper we present several experiments in order to investigate the spatial pattern of the heterogeneous autoregressive coefficients estimated for unemployment data for German NUTS-3 regions.

Keywords: unemployment persistence, dynamic panel, hysteresis, spatial filtering, fixed effects

JEL codes: C21, C23, R12

1. Introduction

Disparities in economic development and welfare *within* countries (at the regional level) are often bigger than *between* countries (Elhorst 1995; Taylor and Bradley 1997; Ertur and Le Gallo 2003; Patuelli 2007; see, for example, the cases of Germany and Italy). In particular, strong and persistent regional disparities in economic performance, unemployment and participation rates are major problems for both local and national policy makers. Spatial disparities occur in both developed and developing countries; their genesis may date back far in history, while their removal may take generations. For decades, spatial disparities have been a source of policy concern and applied research (for a recent overview of this field, see Kochendörfer-Lucius and Pleskovic 2009). Underperforming regions imply, for the (redistributive) state, the need to allocate a higher share of public spending to those regions, eventually creating distortions in the redistribution of tax revenues, and increased conflict with local policy makers and the public. Additionally, high unemployment has historically been linked to a number of socioeconomic problems, such as single-parent households, underperformance of students in school, truancy rates, and more (Armstrong and Taylor 2000). Persistently high unemployment rates have been shown to be correlated with high shares of long-term unemployment and outmigration (for example, recent data for Southern Italy show an increase in the outmigration – toward the North – of the top university graduates; see SVIMEZ 2009).

In particular, with regard to regional unemployment disparities, policy makers need, in order to correctly target their actions and policies, to understand two aspects of such disparities: (a) the determinants of unemployment persistence and variation; and, (b) the region-specific and the cross-regional dynamics of unemployment. On the one hand, the determinants of unemployment have been studied extensively in the regional economic literature (Taylor and Bradley 1997; Badinger and Url 2002; Aragon et al. 2003; Elhorst 2003; Niebuhr 2003; Basile and De Benedictis 2008; Oud et al. 2008; Nijkamp 2009). On the other hand, less attention has been devoted to the dynamics of regional unemployment, and to each region's sensitivity to shocks, seasonal factors, and persistence of unemployment. The available literature is mostly focusing on a macroeconomic setting, such as in a (conditional/unconditional) 'convergence towards a natural rate of unemployment' perspective (see, for example, Decressin and Fatás 1995; Bayer and Juessen 2007; Tyrowicz and Wojcik 2009c, b, a), or in search of the non-accelerating inflation rate of unemployment (NAIRU). Similarly, the correlation of unemployment rates in space – that is, between neighbouring regions – has been studied both in an exploratory/descriptive fashion (Molho 1995; López-Bazo et al. 2002; Cracolici et al. 2007; Mayor and López 2008; Patuelli et al. 2009), and with regard to the determinants of unemployment (Elhorst 1995; Mitchell and Bill 2004; Kosfeld and Dreger 2006; Patacchini and Zenou 2007; Aldashev 2009), employing spatial-econometric techniques.

Less effort has been made, aside from in a time series context (Schanne et al. 2009), to decompose the spatial dynamics of unemployment, so that region-specific autoregressive processes (responses to shocks), or region-specific seasonal characteristics can be traced. However, besides the old and general story that regions are not isolated islands, some specific arguments exist for regional interdependence in the development of unemployment. Commuting costs affect the search radius and the search intensity of the unemployed (Patacchini and Zenou 2005, 2007). Information regarding vacancies is likely to decline with distance – that is, an unemployed individual hardly or never learns about jobs available far away. Furthermore, regional accessibility not only has an impact on the aggregate level of unemployment, but also on individuals' unemployment duration (Détang-Dessendre and Gaigné 2009). As productivity and employability (that is, the chance of getting a job at a certain wage-productivity combination) decrease with unemployment duration, persistence tends to increase (Pissarides 1989). With regard to the urban-rural patterns of unemployment and their dynamics: more jobs are located in the cities than in the rural areas, as periphery-to-core commuting indicates. Thus, the local vacancy-to-unemployment ratio could be expected to be more favourable in cities. However, peripheral regions located between two or more cities could be better off in labour market tightness terms, if vacancies in nearby regions are taken into account; the spatial vacancy-to-unemployment ratio may be inversely related to local tightness. Because the unemployed in peripheral regions are less focused on their own local labour markets, these regions may be able to adapt more quickly to shocks.

Policy makers who understand the specific characteristics of a region and of interregional dependencies are able to tackle problems more effectively, and to anticipate more accurately necessary reactions to aggregate and local shocks. Likewise, a group of (contiguous) regions that share common characteristics has the opportunity to develop common strategies (for example, within a single macro-region, such as a German *Bundesland*). We stress the need to investigate (break down) the components of region-specific dynamics, from an autoregressive/reaction-to-shocks viewpoint, so as to identify spatial patterns of common characteristics.

This paper develops a number of autoregressive models for analysing regional unemployment between 1996 and 2004 in the 439 German NUTS-3 regions (*kreise*). Because these are actual administrative regions, they can be considered an ideal unit of analysis, because they directly relate to local policy-making choices. We estimate autoregressive effects specific both to each administrative region and to different urbanization and agglomeration degrees of regions. In addition to a standard fixed effects (FE) estimation approach, we propose an econometric procedure suggesting the use of spatial filtering (SF) techniques as a substitute for FE in a panel estimation framework. The spatial filter computed here is a proxy for spatially distributed region-specific information (e.g., the endowment of natural resources or the size of the 'home market') that is usually incorporated in the FE coefficients. The approach presented here is beneficial because it allows considerable savings in terms of degrees of freedom, as well as a straightforward interpretation – as the linear combination of orthogonal spatial patterns – of the FE components surrogate. By incorporating region-specific information that generates spatial autocorrelation and dynamics, our procedure provides insights about the spatial patterns within spatiotemporal processes, such as GDP growth/convergence, house price diffusion, and spread of diseases.

In this paper, we present several experiments investigating the spatial patterns of autoregressive coefficients estimated for the unemployment rates of German NUTS-3 regions. The rest of the paper is structured as follows. Section 2 describes the analytical design of the paper. Sections 3 and 4 present the dataset used and the results obtained, respectively. Finally, Section 5 provides a rejoinder and conclusive remarks.

2. Analytical Design of the Model

2.1. The Traditional Approach

The current standard approach to analyse the persistence of unemployment or, in a multi-region context, its convergence speed (see, for a recent overview, Lee and Chang 2008) is to estimate a system of AR(1) processes, and to test each single equation as well as the entire system of equations for unit roots. Here, the basic equation for unemployment u in region i is given by:

$$u_{i,t} = \alpha_i u_{i,t-1} + \mu_i + s_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where μ_i denotes the average unemployment,[1] $s_{i,t}$ its seasonal component, and $\varepsilon_{i,t}$ an i.i.d. mean-zero random disturbance. Stacked over all regions, this set can be written as the following system of equations:

$$U_t \iota_N = U_{t-1} A_N + M_N + S_t + \varepsilon_t, \tag{2}$$

with $U_t = diag_{i=1}^{N}(u_{i,t}), A_N = (\alpha_1, \ldots, \alpha_N)'$, $M_N = (\mu_1, \ldots, \mu_N)'$, $S_t = (S_{1,t}, \ldots, S_{N,t})'$, $\iota_N = (1, \ldots, 1)'$ a unit vector of length N, and $\varepsilon_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{N,t})'$. The subscript N in A_N and M_N denotes the length of the coefficient vectors. Vectors and matrices with subscript t always have length N; we omit the N subscript in order to distinguish between a vector (for example, ε_t) and its Nth element ($\varepsilon_{N,t}$). M_N is equivalent to FE in a panel framework.

The process in region i has a unit root if the autoregressive parameter α_i equals one. A single equation is tested for stationarity by augmented Dickey-Fuller (ADF) tests, or by Phillips-Perron (PP) tests; likewise, various tests derived for panels or systems that rely as well on subtracting lagged unemployment from both sides of Equation (2) require the following form of Equation (2):

$$(U_t - U_{t-1})\iota_N = U_{t-1}(A_N - \iota_N) + M_N + S_t + \varepsilon_t, \tag{3}$$

Next, we may test if the elements of $(A_N - \iota_N)$ are, individually or jointly, significantly less than zero.[2] Some procedures test the entire set of coefficients directly (for example, Sarno and Taylor 1998), whereas others combine the individual t-statistics to form a joint test statistic (see Maddala and Wu 1999 or Im et al. 2003). Furthermore, restrictions may be imposed on the coefficient and, for example, enabling a test only for stationarity of the average autoregressive process, as in Levin et al. (2002), or for the stationarity of a limited number of regime-specific processes (also referred to as the ‘convergence clubs’ hypothesis).

Regarding the validity of panel unit-root tests, most of these procedures require the time dimension to be sufficiently large in order to converge and not to be plagued by the so-called Nickell bias arising in small time-series (Nickell 1981). Moreover, Equations (2) and (3) are only estimable in a seemingly unrelated regression (SURE) form (that is, in a specification

[1] We assume that unemployment does not have a deterministic trend.

[2] The coefficients $\alpha_i - 1$ follow, under the null hypothesis of a non-stationary process, a non-normal degenerate distribution, typically a Wiener process (also denoted as Brownian motion).

that allows for simultaneously correlated errors) when the number of regions is small, or else one has to assume independence of the regions, resulting in equation-wise unit-root tests with low efficiency/power. Nonetheless, cross-sectional correlation seems rather plausible, in particular when considering small spatial units, and taking this structure into account in the error term ε_t is preferable.

Cross-sectional (spatial) correlation arises not only in contemporaneous shocks, but also in levels and trends (as shown in Table 1), in seasonal patterns, or in the adjustment speed. On the one hand, these spatial patterns or correlations could likewise be utilized to get better – more efficient, more powerful, less demanding in terms of degrees of freedom, and large-N, small-T consistent – estimates of the average convergence speed. On the other hand, knowledge about spatial interdependence between the structures of a time-series – average/trend, seasonality, and autoregressive properties – may be of direct interest as well.

Table 1. Descriptive statistics of regional unemployment, 1996–2004

Region	*Mean*	*St. dev.*	*1st quartile*	*Median*	*3rd quartile*	*MI*
Unemployment rates (levels, in %)						
Germany	11.8	5.5	7.6	10.1	15.4	0.903
East	19.4	3.5	17.0	19.3	21.8	
North	11.1	2.8	9.0	10.7	13.0	
South	8.1	2.5	6.2	7.7	9.5	
First differences (in %)						
Germany	0.01	1.21	–0.43	0.11	0.59	0.623
East	0.06	1.76	–0.88	0.30	1.22	
North	–0.01	0.89	–0.34	0.06	0.40	
South	–0.06	0.88	–0.72	–0.07	0.60	

In the following, we propose an alternative approach to estimating Equation (2), which decomposes the autoregressive processes according to exogenous spatial patterns that are representative of accessibility/contiguity relations between the regions studied. The benefit is dual: (a) we obtain an explicit model of the spatial patterns in unemployment without being over-restrictive by imposing (probably erroneous) regime-specific constraints; and, (b) we are able to estimate more parsimoniously while covering the most relevant spatial structures.[3]

2.2. Spatial Filtering

A wide array of methods, as well as several dedicated 'spatial' econometric procedures, for the statistical analysis of georeferenced data is available in the literature. Most commonly employed, spatial autoregressive techniques (see, for example, Anselin 1988) model interregional dependence explicitly by means of spatial weights matrices that provide measures of the spatial linkages between values of georeferenced variables, with a structure similar to serial correlation in time-series econometrics.

An alternative approach to spatial autoregression, modelling spatial autocorrelation in the mean response rather than in the variance, is the use of spatial filtering (SF) techniques (Getis and Griffith 2002). Their advantage is that the studied variables (which are initially spatially correlated) are split into spatial and non-spatial components. Then these components can be employed in a linear regression framework. In addition, filtering out spatially autocorrelated patterns enables a reduction in the stochastic noise normally found in the residuals of standard statistical tools such as OLS. This conversion procedure requires the computation of a 'spatial filter'.

The SF technique introduced by Griffith (2003) is based on the computational formula of Moran's I (MI) statistic.[4] This eigenvector decomposition technique extracts n orthogonal, as well as uncorrelated, numerical components from the $n \times n$ modified spatial weights matrix

$$W = (I_n - \iota\iota'/n)C(I_n - \iota\iota'/n), \tag{4}$$

where I_n is an identity matrix of dimension n, ι is an n × 1 unit vector, and C is a spatial weights matrix[5] representing the spatial relation between each pair of regions; matrix $(I_n - \iota\iota'/n)$ is the standard projection matrix found in the multivariate statistics and regression

[3] This claim clearly needs to be further supported by simulation evidence that SF is equivalent when substituting/approximating fixed effects.

[4] Moran's I is calculated as follows:

$$I = \frac{N\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_i \sum_j w_{ij})\sum_i (x_i - \bar{x})^2},$$

where, in the case of a set of N regions, x_i is the value of the generic variable x in region i, and w_{ij} is the cell (i, j) of a spatial weights matrix W, indicating the proximity of each pair of regions i and j.

[5] For a discussion of coding schemes and proximity definitions, see Patuelli (2007).

literature. The eigenvectors are extracted in a decreasing order of their partial contribution to MI, the first corresponding to the largest eigenvalue of W. Thus, the first two eigenvectors computed (E_1 and E_2) often identify map patterns along the cardinal points (that is, some rotated version of the major North-South and East-West patterns). Eigenvectors with intermediate values of MI display regional map patterns, whereas eigenvectors with smaller values of MI display local map patterns. The set of relevant eigenvectors – those explaining the spatial pattern in the variable of interest – can be found by regressing the dependent variable on the eigenvectors in a stepwise fashion, retaining the significant eigenvectors (or eliminating the insignificant ones). The linear combination of selected eigenvectors and their corresponding coefficient estimates define the spatial filter for the variable of interest. In an autoregressive setting (where no covariates are employed), residuals obtained with stepwise regression constitute the spatially filtered component of the georeferenced variable examined (see Griffith 2000). The eigenvectors can be seen as independent map patterns that coincide with the latent spatial autocorrelation of a given georeferenced variable, according to a given spatial weights matrix. Moreover, they can work as proxies for omitted variables that show a certain coincidence or similarity regarding their spatial distribution.

Griffith (2008) shows that SF not only refers to the unobserved spatial correlation of a variable, but also contributes to the explanation of spatial heterogeneity in the coefficients. An equivalent to the coefficients of a geographically weighted regression (GWR, Brunsdon et al. 1998) can be computed by introducing interaction terms between the exogenous variables of an equation and the eigenvectors extracted from a spatial weights matrix into a model specification.

2.3. An Adjustment-Process Spatial Filter

The coefficients α_i and μ_i in Equations (2) and (3) can be expected to show spatial heterogeneity and/or autocorrelation, a pattern in space that may be related to the structure of a spatial weights matrix, and for which they could be tested, for example, by computing these coefficients' MI. These spatial patterns can be and preferably should be considered explicitly instead of in the parameter-intensive formulation of heterogeneity given in Equations (2) and (3). We introduce spatial patterns by replacing the terms A_N and/or M_N by $A_N = \omega\tilde{A}_K + \eta_N$ and $M_N = \omega\tilde{M}_K + \nu_N$, where ω is a set of eigenvectors E_k extracted from the normalized spatial weights matrix given in Equation (4) (Griffith 2003). Because matrix C is pre- and postmultiplied by the projection matrix [see Equation (4)], these eigenvectors are centred at zero. For notational simplicity, ω collects the constant (that is, ι_N) as well, because also $\frac{1}{\sqrt{n}}\iota_N$ is also an eigenvector of matrix W. We define $\omega = (\iota_N, E_1, \ldots, E_{K-1})$ as a matrix of size $N \times K$. η_N and ν_N are assumed to contain non-spatial patterns within the individual coefficients that have zero mean and are orthogonal to the spatial process, and can thus move to the residuals. As we can substitute both the level and the dynamic adjustment in a process by their spatial counterparts, three alternative specifications to Equation (2) yield

$$U_t\iota_N = U_{t-1}A_N + \omega\tilde{M}_K + \nu_N + S_t + \varepsilon_t; \tag{5}$$

$$U_t\iota_N = (U_{t-1}\omega)\tilde{A}_K + U_{t-1}\eta_N + M_N + S_t + \varepsilon_t; \text{ and,} \tag{6}$$

$$U_t\iota_N = (U_{t-1}\omega)\tilde{A}_K + U_{t-1}\eta_N + \omega\tilde{M}_K + \nu_N + S_t + \varepsilon_t. \tag{7}$$

Equation (5) is the SF equivalent to the FE panel estimation [see Equation (2)]. In contrast, Equations (6) and (7) show similarities with the SF representation of GWR (Griffith 2008). $\tilde{\alpha}_1$, the first element of the coefficients vector $\tilde{A}_K$, and the one linked to the constant, estimates the average adjustment speed. The further autoregressive coefficients specify regional patterns in the adjustment speed; for example, the coefficients for the interaction terms between lagged unemployment and eigenvectors E_1 and E_2 reflect differences in the adjustment speed along the cardinal coordinates, similarly to the patterns that the eigenvectors themselves represent for the levels.

The new residuals vector – for example, defined as $\zeta_t = U_{t-1}\eta_N + \nu_N + \varepsilon_t$ in Equation (7) – may exhibit either a panel-specific mean-zero component (a random effect, when $\sigma_\nu^2 > 0$), or panel-specific serial correlation in the residuals (when $\sigma_\eta^2 > 0$). Nonetheless, the orthogonality between the spatial eigenvectors and the non-spatial time-constant component suffices to guarantee orthogonality between the regressors $(U_{t-1}\omega, \omega)$ and ζ_t; that is, consistency of the estimation of Equations (5), (6) and (7). However, the overall variance of these equations is inflated by the variance of ν_N and/or $U_{t-1}\eta_t$ with respect to Equation (2).

2.4. Spatial Regimes

An alternative approach to studying spatial heterogeneity in coefficients is the introduction of explicit spatial regimes that, for example, distinguish between urban and rural economies, or to have one regime for each federal state (covering all districts within a single state). The number of spatial regimes to use is rather heuristic. Because such schemes allow results to be interpreted as a structural break (Anselin 1990), a common choice in applied work is to use just two regimes: typically, North versus South for Europe (Ertur et al. 2006), or East versus West for Germany. In this paper, we apply a classification of regions by the German Federal Bureau for Construction and Regional Planning (*Bundesamt für Bauwesen und Raumordnung*, BBR), which identifies nine different degrees of urbanization and agglomeration.[6] The intuition is that cities or agglomerations – which have a different industrial and firm structure, different information channels, and populations with different preferences than rural areas – adjust to shocks differently than do rural areas.

In our analysis, we differentiate the (serial) autoregressive coefficients (and seasonal effects) according to the nine spatial regimes, and follow the previous estimation approaches for the region-specific levels (by FE or SF). Thus, let D_{class} denote the $N \times R$ matrix that assigns a certain urbanization/agglomeration class to each region. In order to avoid perfect multicollinearity, there is no average autoregressive effect included in the equation system. ξ_N is the part of spatial heterogeneity in the autoregressive process that is not covered by the regimes, and that is considered unobservable. Then, the two spatial-regimes specifications are given by

$$U_t \iota_N = (U_{t-1} D_{\text{class}}) \widehat{A}_R + M_N + U_{t-1} \xi_N + S_t + \varepsilon_t; \text{ and} \tag{8}$$

$$U_t \iota_N = (U_{t-1} D_{\text{class}}) \widehat{A}_R + \omega \tilde{M}_K + U_{t-1} \xi_N + v_N + S_t + \varepsilon_t. \tag{9}$$

In summary, we present three different approaches to model spatially heterogeneous autoregressive processes: by individual, spatial-filtering, and spatial-regimes coefficients. In addition, we can estimate a homogeneous coefficient as well, as in a standard dynamic panel. The length of the coefficient vector $\tilde{A}_K$ in the SF autoregressive model is $1 < K \leq N$; that is, there are more parameters than in the homogeneous model (with $\alpha_i = \bar{\alpha}$) and, typically, much

[6] The nine classes are: (1) central cities in regions with urban agglomerations; (2) highly-urbanized districts in regions with urban agglomerations; (3) urbanized districts in regions with urban agglomerations; (4) rural districts in regions with urban agglomerations; (5) central cities in regions with tendencies towards agglomeration; (6) highly-urbanized districts in regions with tendencies towards agglomeration; (7) rural districts in regions with tendencies towards agglomeration; (8) urbanized districts in regions with rural features; and (9) rural districts in regions with rural features.

less than in the heterogeneous model of Equation (2). Likewise, the number of spatial-regimes autoregressive coefficients is $1 < R < N$. Thus, both the SF and the spatial-regimes autoregressive models are more parsimonious than the individual model.

Theoretically, all other model components are possible to modulate – deterministic mean and seasonal effects – according to the same four schemes. Instead of considering all 64 possible models, in this paper we analyse only specifications where the deterministic mean is represented by FE or the spatial filter, and with homogeneous versus individual (region-specific) autoregressive and seasonal effects.

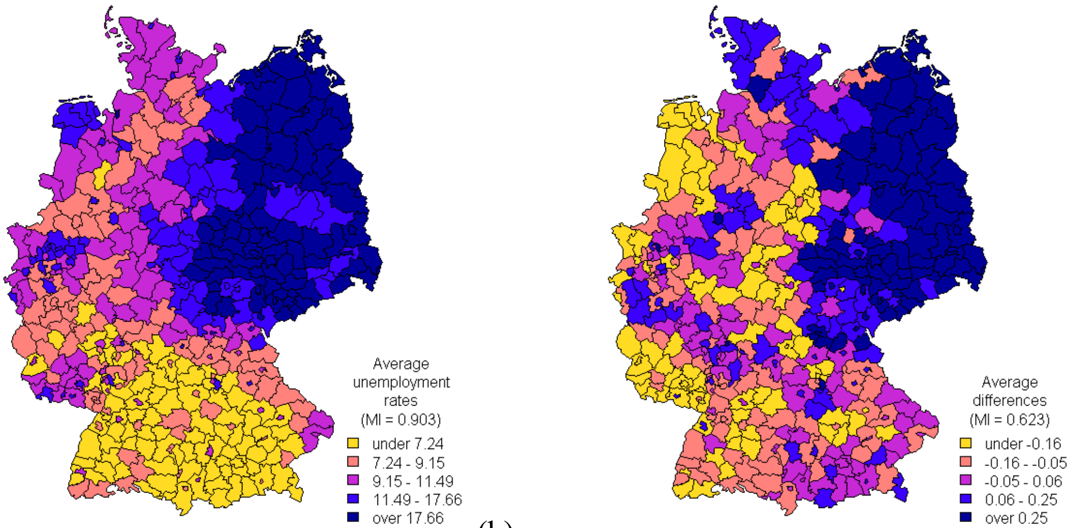
3. Data

Analyses in this paper employ data about German regional unemployment rates, at the NUTS-3 level of geographical aggregation (*kreise*, denominated 'districts' hereforth). The data are available for all 439 districts, on a quarterly basis, for the years 1996 to 2004.[7]

Summary statistics for the data at hand are presented in Table 1. The table results confirm that high and low (regional) unemployment rates are not randomly distributed across Germany. A first examination of the data suggests an asymmetric distribution, which is skewed toward high unemployment rates (the difference between the median and the third quartile is almost one standard deviation). When inspected spatially, the data show marked spatial autocorrelation (Moran's I (MI) for the districts' average unemployment is 0.878), which is further confirmed by descriptive statistics calculated for macro-regional subsets, and by the map in Figure 1a. While the former East Germany shows high unemployment rates (averaging 19.4 per cent) with (apparently) little variation (the first quartile is 17 per cent), the former West Germany shows low-to-moderate rates in the North (Northrhine-Westfalia, Lower Saxony, Schleswig-Holstein, and the city-states of Bremen and Hamburg) and in the South (Bavaria, Baden-Wurttemberg, Hesse, Rhineland-Palatinate, and the Saarland). When differencing the data, one can note that a certain amount of spatial autocorrelation remains (MI = 0.531), suggesting that not only the levels of unemployment, but also the dynamics, are

[7] The recently formed East German district of *Eisenach* (ID 16056) belonged to the *Wartburgkreis* district (ID 16063) until the end of 1997. Thus, unemployment rates for *Eisenach* before 1998 are not available, and we set them equal to the ones of *Wartburgkreis*. Also, in the first quarter of 1996, labour force figures are not available for five East German regions. In order to compute unemployment rates, we set the labour force (the denominator of the rate) equal to the labour force reported in the subsequent four quarters (as it is determined only once per year by micro-census data).

spatially correlated. Again, this feature is evident in Figure 1b. This first finding implies that, when estimating a simple AR(1) panel model, one should expect spatial autocorrelation, as well as group-specific serial correlation, in the residuals.



(a) (b)

Figure 1. Quantile maps of average unemployment rates: in levels (a) and in one-year differences (b)

A further visualization of the data, following Peng (2008), allows a plot of all data (15,804 records) simultaneously, providing a bird's eye view over regional disparities and trends. Figure 2a shows the unemployment rates of all German districts, by using a common colour scheme, where the different shadings are based on quantiles of the pooled data, and darker shades indicate higher unemployment. The graph (and the accompanying box plots) clearly shows that East German districts (bottom rows of each graph) have significantly higher unemployment. Seasonal effects are visible in the background, as the winter quarters show consistently higher unemployment (regularly occurring darker columns).

Assigning to each district its own colour scheme (based on each time series' quantiles), renders Figure 2b. Although most West German districts appear to have had their best performance (that is, lowest unemployment rates) between 2000 and 2002, this is not the case for the East German districts. Instead, they seem to have had lower unemployment in 1996.[8] Figure 2c and 2d provide corresponding plots for one-year differences of the data. Noteworthy is the variance of the unemployment variations, plotted in the right margin, which

[8] In this regard, it should be recalled that no NUTS-3-level unemployment data are available for East Germany before 1996.

is much higher for East German districts (also because it is not standardized), as highlighted in Table 1.

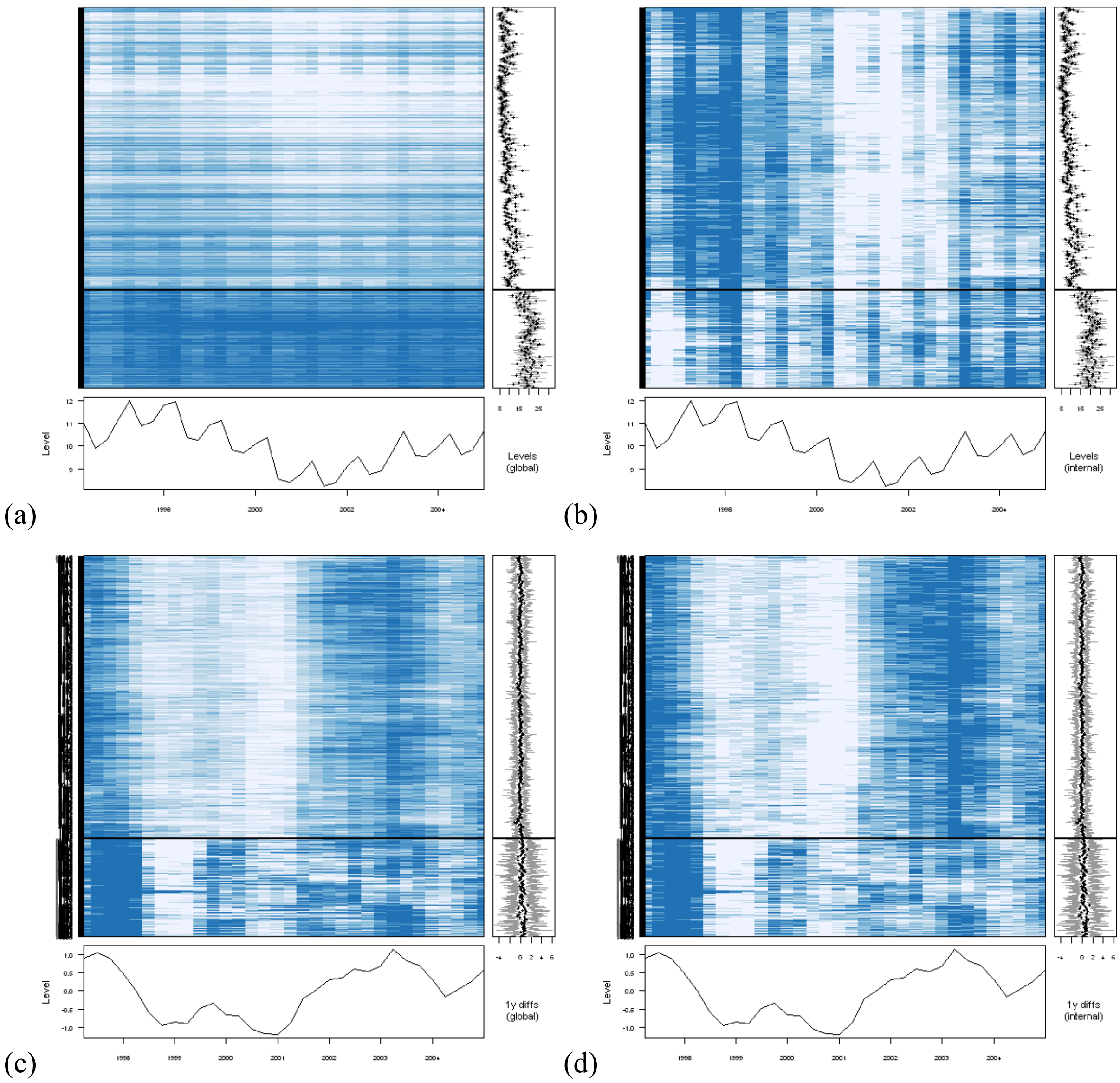


Figure 2. Visual representation of German regional unemployment rates. Top graphs show levels, bottom graphs show one-year differences; in left graphs, colour scheme is common, in right graphs is region-specific. Thick line separates West German (above) and East German (below) districts. Right margin shows box plots for each district's time series. Bottom margin shows median features

4. Empirical Application

4.1. Fixed Effects and Spatial Filter Estimation

In the preceding discussion, we present a class of dynamic panel models, ranging from standard FE estimation (Equation (2)) to an alternative approach based on surrogating the FE by means of a spatial filter (Equation (5)), to GWR-type spatial filter and spatial regimes models. This subsection presents and compares results obtained for the first (FE and SF) approaches mentioned for a class of models with homogeneous and/or heterogeneous estimates of AR(1) coefficients and seasonal effects. In particular, in Table 2, we compare summary results such as measures of fit (R^2 and RMSE), (average) autoregressive coefficients estimated by the two approaches, and spatial autocorrelation in regression residuals.

The top left panel of Table 2 compares the most basic model specifications in terms of autoregressive coefficients, in which just one (homogeneous) AR(1) parameter is estimated, assuming $\alpha_1 = \alpha_2 = \ldots = \alpha_N$. The FE and SF approaches are then compared. We find that the computed AR(1) coefficients differ between the two approaches. The FE estimation returns an AR(1) coefficient of 0.766, while the SF estimation gives a higher coefficient of 0.945. The reasons for this difference in estimate are to be sought in the differences between the FE and SF estimates, and may be explained in terms of the heterogeneous AR process case. In terms of model fit, the SF estimate provides a fit to the data – in terms of R^2 – very similar to the one for the FE estimate (0.975 versus 0.977), while saving about 400 degrees of freedom. As stated in Section 2.3, the variance of the SF estimation is deemed to be (slightly) inflated with respect to the FE variance, which is also suggested by the computation of the RMSE (this is true for all estimations presented in Table 2). Meanwhile, in Figure 3 we can see how the SF computed (as the linear combination of the 39 eigenvectors selected) approximates the spatial patterns shown in the FE coefficients. The spatial patterns shown in the two maps may be expected to include both region-specific variations from the average (homogeneous) AR(1) coefficient and seasonal effects, as well as unobserved variables (such as, for example, other lags of the unemployment rate).

Finally, the levels of residual spatial autocorrelation appear to be similar for the FE and SF approaches, with a tendency for the SF approach to obtain residuals slightly less correlated in space. The time-averaged residual per region is zero or very close to zero, and spatial autocorrelation is absent. Consequently, quarter-specific spatial autocorrelation can be related directly to each quarter's specific shocks or unobserved characteristics (beyond direct seasonal effects, which are included in the model), and no recurring pattern exists over time. This finding is also suggested by the maps of the residuals of the FE estimation shown in Figure 4. The SF approach provides similarly varying geographical patterns in the residuals.

Table 2. Selected results for the homogeneous and heterogeneous AR process models

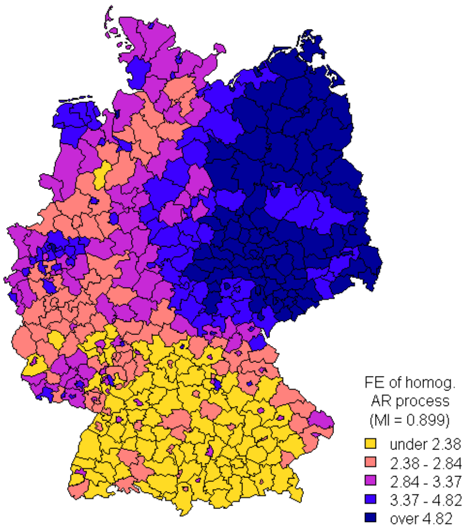
Level	*Homogeneous seasonality*		*Heterogeneous seasonal effects*	
	FE	*SF*	*FE*	*SF*
Homogeneous AR(1) process: $\bar{\alpha}$				
AR(1) coeff.	0.766	0.945	0.901	0.957
Av. residuals MI	0.489	0.482	0.357	0.317
Min. residuals MI	0.195	0.204	0.142	0.038
Max residuals MI	0.775	0.734	0.754	0.767
R^2	0.977	0.975	0.992	0.991
RMSE	0.827	0.872	0.504	0.530
Res. dfs	14,922	15,321	13,608	13,979
Heterogeneous AR(1) process: $\alpha_i = A_{N_i}$				
Av. AR(1) coeff.	0.833	0.823	0.906	0.914
Min. AR(1) coeff.	0.135 (3462)	0.113 (9271)	0.485 (14181)	0.594 (14188)
Max. AR(1) coeff.	1.120 (5382)	1.275 (5162)	1.035 (5711)	1.137 (9677)
No. of AR(1) >= 1	72/439	79/439	6/439	48/439
No. of AR(1) < 1 (ADF, 5% sign.)	156/439	284/439[9]	97/439	264/439[10]
Av. residuals MI	0.486	0.478	0.369	0.365
Min. residuals MI	0.169	0.094	0.143	0.128
Max residuals MI	0.787	0.804	0.782	0.805
R^2	0.981	0.980	0.992	0.992
RMSE	0.753	0.777	0.493	0.500
Res. dfs	14,484	14,865	13,170	13,564

Subsequently, the bottom left panel of Table 2 provides summary results for estimation of the models presented in Equations (2) and (5), estimating heterogeneous AR(1) coefficients according to the FE and SF approaches, respectively. In contrast with the homogeneous case, where the estimated AR(1) coefficient differed markedly between the two models, the estimates obtained here are rather similar on average, although the number of estimated coefficients greater than or equal to 1 is slightly different: 72 and 79 for the FE and SF

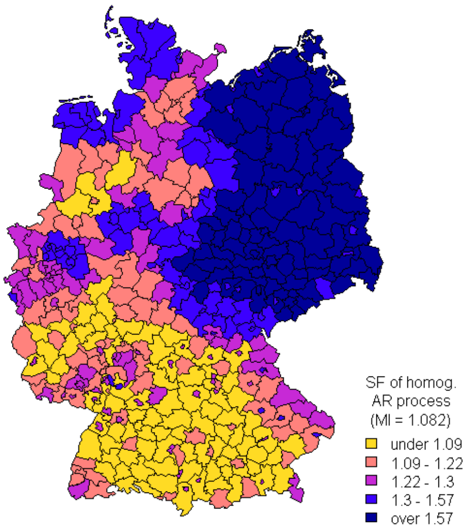
[9] In this case, 18 AR(1) coefficients are found to be significantly bigger than 1 at the 95 per cent confidence level.

[10] In this case, 2 AR(1) coefficients are found to be significantly bigger than 1 at the 95 per cent confidence level.

approaches, respectively. However, more rigorous augmented Dickey-Fuller (ADF) tests suggest that unit roots can be *excluded* (at the 95 per cent confidence level) for 156 districts in the FE approach, and for 284 districts in the SF approach, making the latter a preferable result.



(a)



(b)

Figure 3. Quantile maps of the FE (a) and SF (b) computed for the homogeneous AR(1) process

Indeed, a certain level of numerical differences may be expected between the two vectors of AR(1) coefficients. The number of eigenvectors selected between a direct extraction of the SF (the procedure followed in this paper) and an indirect procedure, where FE are computed first, and an SF is extracted from the FE coefficients vector. In the former case, fewer eigenvectors are selected, most likely because of the error component ε_t (see Equation (2)) not being considered in the indirect procedure. In contrast, a number of eigenvectors often are selected only in the direct procedure, suggesting correlation between these eigenvectors and the covariates (for example, U_{t-1} is *not* assumed to be orthogonal to the eigenvectors). Consequently, possible differences exist between the AR(1) vectors of coefficients for Equations (2) and (5). The extent of these differences depends on each specific case, and their direction remains to be fully inspected with a simulation experiment. With regard to the present analysis, differences appear to be mostly in the extremes, as shown by the similar quantiles and geographical patterns appearing in Figure 5. Both maps indicate higher first-quarter autoregressive effects in the western urbanized areas going (South to North) from Munich to the Stuttgart and Mannheim areas, to the Ruhr and Rhine areas, to Bremen, patterns that generally resemble the spatial distribution of population density in Germany.

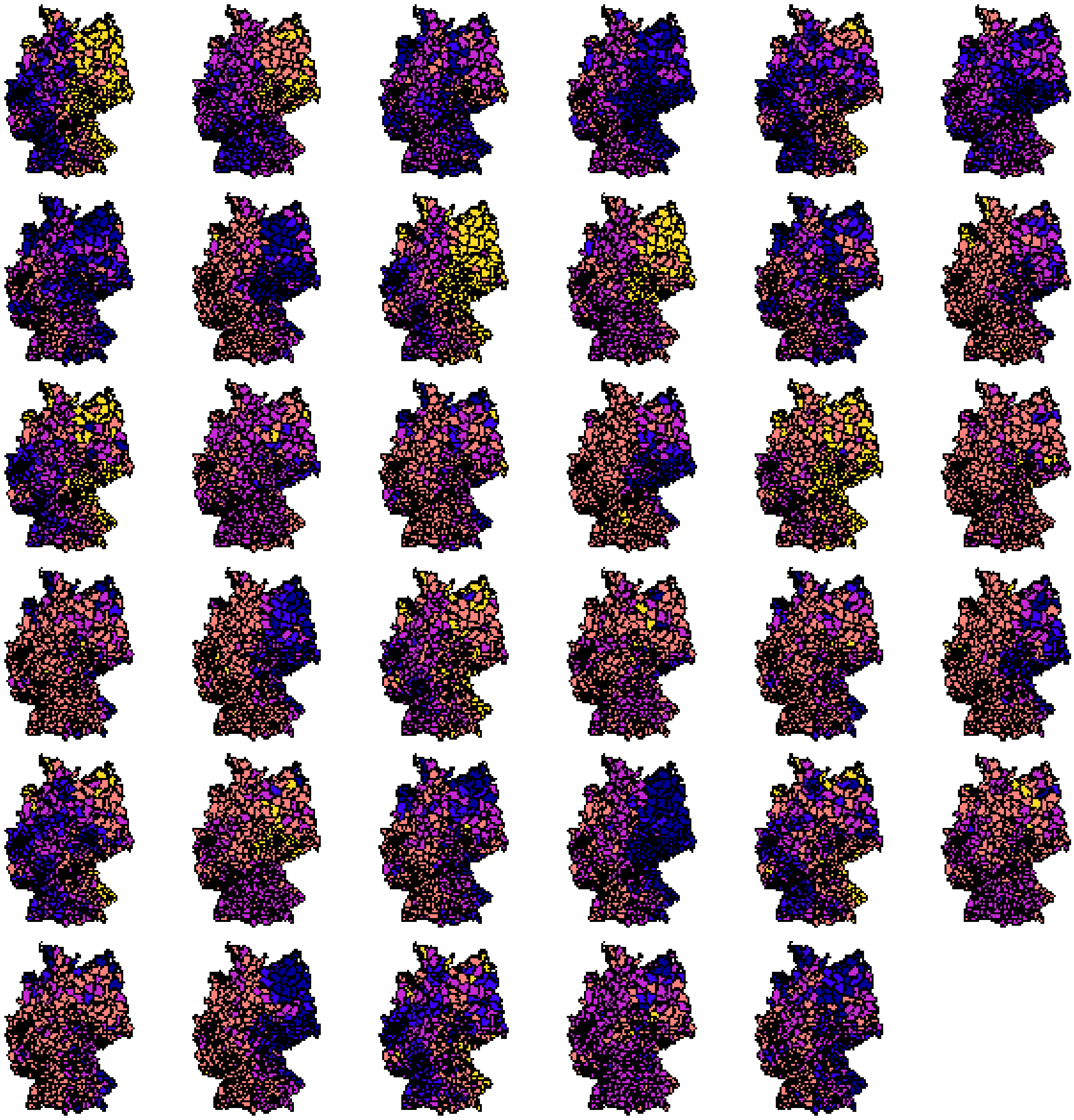
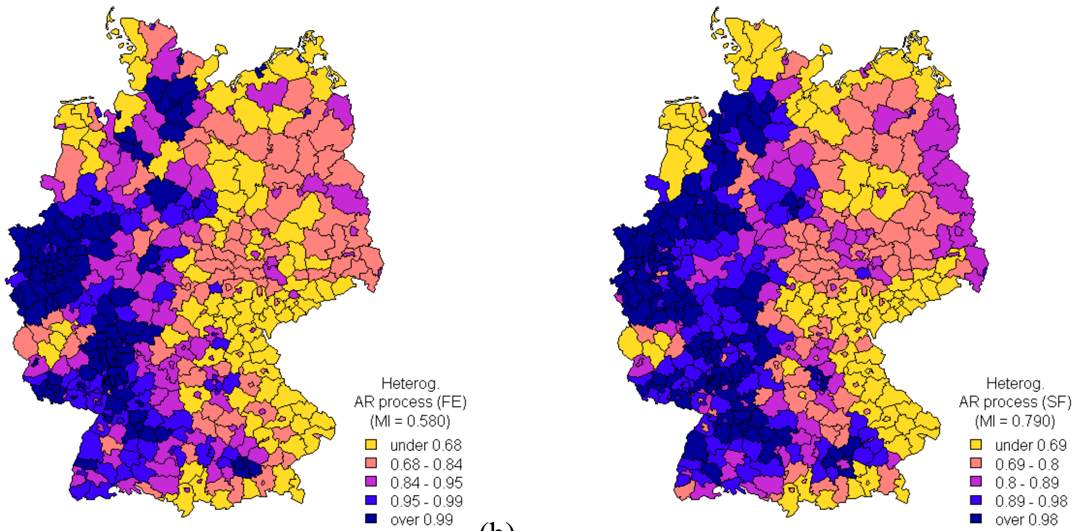


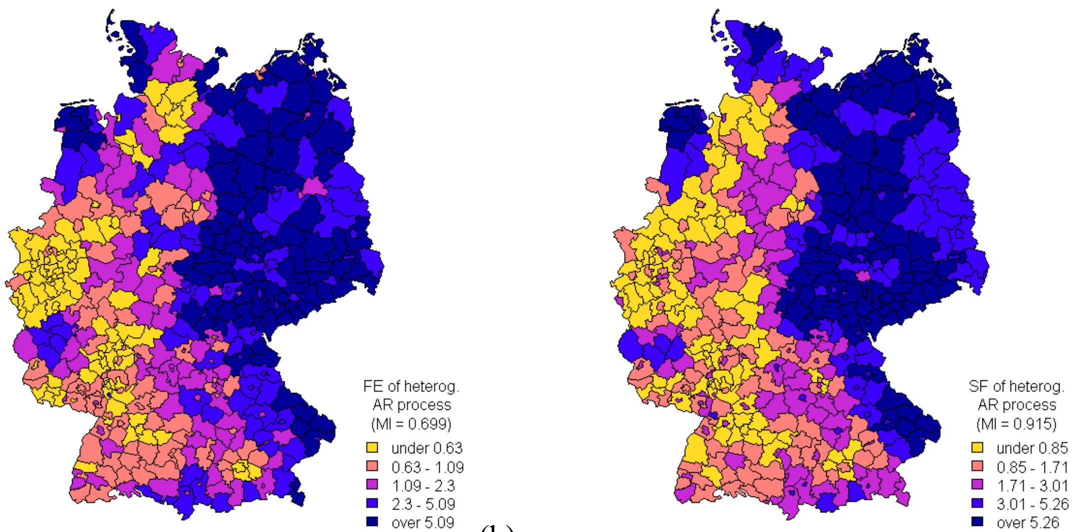
Figure 4. Quantile maps of residuals computed for the homogeneous AR(1) process (FE approach)

Conceivably, once we let the autoregressive coefficient vary over the cross-section of districts, the measures of fit of the models (R^2 and RMSE) improve, while 438 (that is, $N - 1$) additional degrees of freedom are consumed. Again, the SF estimation allows us to save about 420 degrees of freedom, while approximating closely the spatial patterns included in the FE coefficients (Figure 6). Finally, residual spatial autocorrelation is the same – on average – in both the homogeneous and heterogeneous AR(1) coefficient estimates, with the SF exhibiting lower minima in this regard.



(a) (b)

Figure 5. Quantile maps of estimated heterogeneous AR(1) coefficients: FE (a) and SF (b) approaches



(a) (b)

Figure 6. Quantile maps of the FE (a) and SF (b) computed for the heterogeneous AR(1) process

Finally, the right panels of Table 2 provide additional empirical results, as the above models are extended to include individual (heterogeneous) seasonal effects. This extension implies computing (439 * 3 =) 1,317 regression coefficients rather than the three previously computed seasonal coefficients (for spring, summer and fall, while winter is used as the reference category). In the case in which both the autoregressive and seasonal effects are computed for each district, which we use as our example in the following discussion, (439 * 4 + 1 =) 1,757 coefficients are computed, which increase to (439 * 5 =) 2,195 in the FE case.[11] As a result, improved fit (higher R^2 and lower RMSE) as well as diminished spatial autocorrelation in the residuals may be expected, which is confirmed by the summary statistics reported in Table 2. In addition, higher average AR(1) coefficients are found, though with comparable results in terms of unit roots, as suggested by the ADF test results. Noteworthy are the changes in the spatial distribution of the AR(1) coefficients and of the FE estimates, as shown in Figure 7. Figure 7a, referring to the AR(1) coefficients, portrays patterns appearing in Figure 5 that are more sparse, as the result of individual seasonal effects having been filtered out. Meanwhile, Figure 7b, appears more similar to Figure 6, although it is slightly smoother.

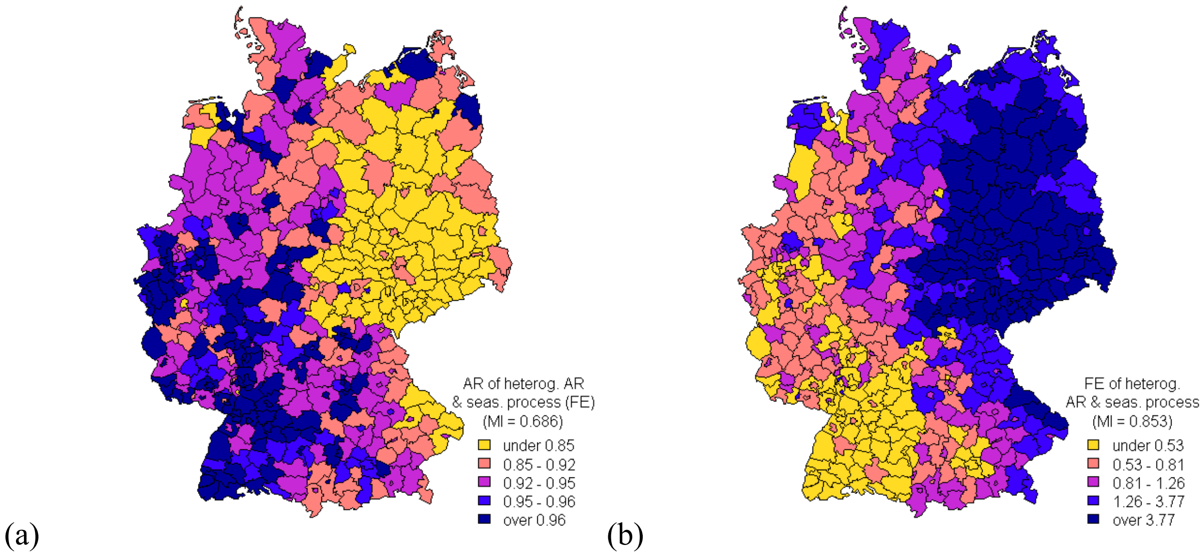


Figure 7. Quantile maps of the heterogeneous AR(1) (a) and FE (b) coefficients computed for the heterogeneous AR(1) and seasonal process (FE estimation)

The analyses presented above suggest that SF may be used to approximate the standard FE estimation for the study of unemployment persistence. Each of the two approaches appears to have specific advantages, allowing a researcher to choose freely between them on the basis of his/her needs. However, further approaches to decomposing region-specific autoregressive effects can be employed, as suggested in Sections 2.3 and 2.4. Results obtained for these additional classes of models are presented next.

[11] Needless to say, the increase in computational load leads to a much slower stepwise selection of the SF, which on the other hand may be improved by the use of faster CPUs, by implementing stepwise solutions suitable for multi-core computers or clusters, or by resorting to different types of model selection procedures (see, for example, Miller 2002).

4.2. Spatial Filter/Fixed Effects in the Autoregressive Component

The maps of the AR(1) coefficients appearing in Figure 5 and the related MI scores highlight that autoregressive coefficients are indeed strongly spatially correlated. As proposed in Section 2.3, the spatial patterns obtained according to Equation (5), by computing N autoregressive coefficients, may be approximated in a GWR-fashion by introducing a spatial-eigenvector specification. Equations (6) and (7) give the FE and SF specifications, respectively, implying that, for the latter, two spatial filters are computed (or, more generally, one for each GWR-type regressor, plus the SF substituting the FE). In our specific case, substituting A_N by its SF representation implies saving 392 degrees of freedom (47 versus 439 AR-related regressors), while extending the GWR-type approach to seasonal effects allows us to save 1,602 degrees of freedom (154 versus 1,756 = 439 * 4), although at the (opportunity) cost of running extensive stepwise regression in order to select the relevant eigenvectors.[12] The relevance of such a huge saving in terms of degrees of freedom becomes evident when considering panels with large N and small T. In addition, the computational intensity of the spatial filter construction only applies to the first estimation of the model, while subsequent estimations – for example, for forecasting purposes – are faster than in the respective cases of Equations (2) and (5), because the relevant eigenvectors already have been selected.

The top panel of Table 3 reports summary statistics for the aforementioned model specifications. The mean, minimum and maximum AR(1) coefficients reported for the GWR-type model (top-left panel) appear to provide a picture similar to the one found in Table 2 for the case of the heterogeneous AR(1) process, with the exception of a higher average coefficient in the SF case. The number of AR(1) coefficients greater than 1 appears to increase here, though this result is not supported by ADF tests.[13] Once again, the levels of spatial autocorrelation in the residuals vary greatly, depending on quarter-specific noise, and are comparable but slightly lower than the earlier ones. RMSE increases moderately, as expected, but is being balanced out by the aforementioned huge savings in terms of degrees of

[12] Given our starting set of 98 candidate eigenvectors, a backward stepwise regression identifying a GWR representation of both the AR(1) coefficients and the seasonal effects evaluates, in the first step, (98 * 4 =) 392 models in the FE case, and (98 * 5 =) 490 models in the SF case.

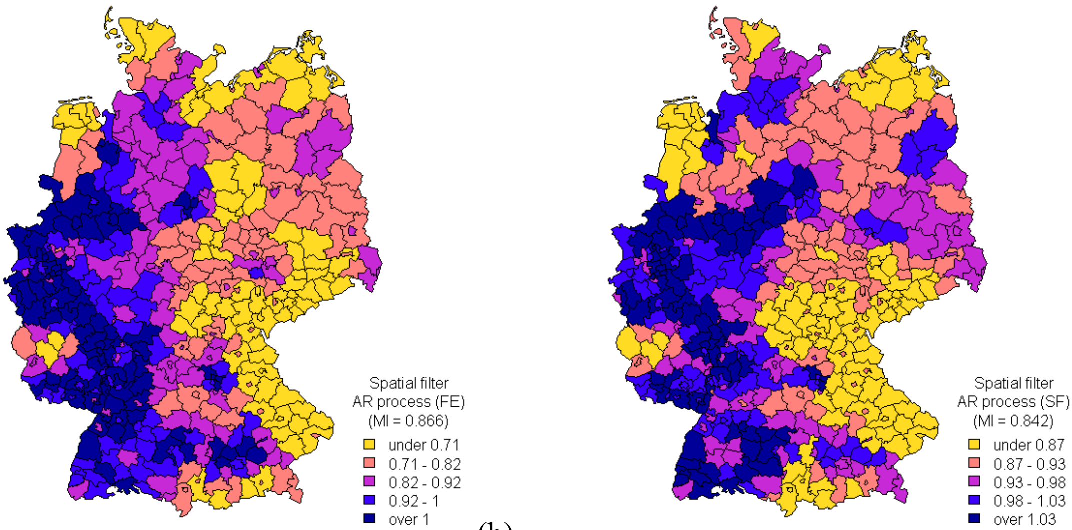
[13] For the GWR-type models, the vector of AR(1) coefficients is obtained as the linear combination of the related eigenvectors, using as weights the regression coefficients computed for the interactions terms between the lagged unemployment rates and the eigenvectors themselves ($\alpha_i = \omega_i \cdot \tilde{A}_K$). Seasonal coefficients for each season, when included, are computed in a similar fashion. Because of this construction, implementing ADF tests is not straightforward, and therefore we omit them here.

freedom. These results are confirmed by extending the GWR specification to seasonal effects (top-right panel).

Table 3. Selected results for the spatial-filter and spatial-regimes AR process models

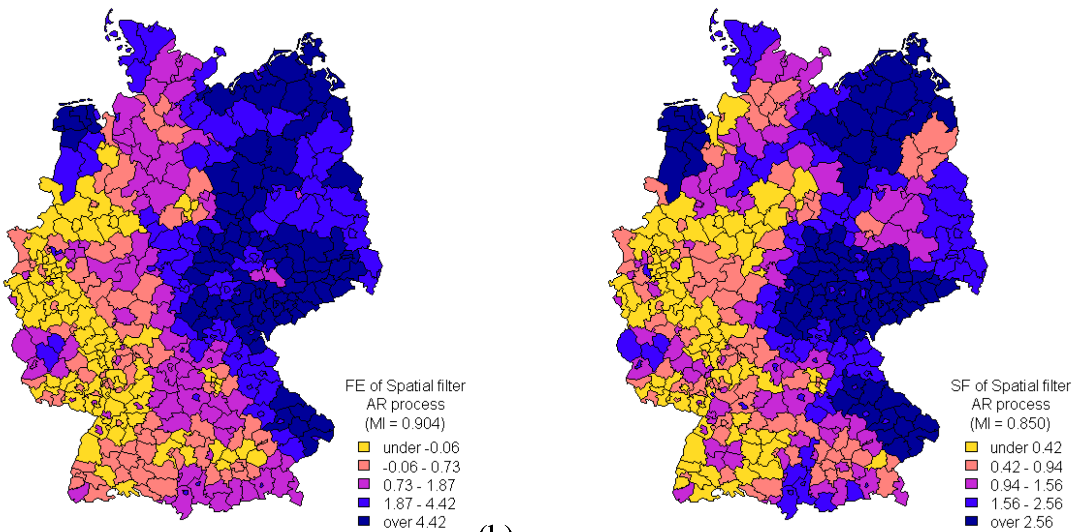
Level	*Heterogeneous AR(1) process*		*Heterogeneous AR(1) process & seasonal effects*	
	FE	*SF*	*FE*	*SF*
	Spatial filter AR(1) process: $\alpha_i = \omega_i \cdot \tilde{A}_K$			
Av. AR(1) coeff.	0.853	0.935	0.882	0.961
Min. AR(1) coeff.	0.162 (9276)	0.276 (9271)	0.530 (14188)	0.697 (9271)
Max. AR(1) coeff.	1.238 (7338)	1.211 (5374)	1.163 (9274)	1.140 (5374)
No. of AR(1) >= 1	94/439	136/439	44/439	94/439
Av. residuals MI	0.481	0.440	0.333	0.176
Min. residuals MI	0.139	0.129	0.012	–0.016
Max residuals MI	0.817	0.730	0.803	0.704
R^2	0.980	0.978	0.985	0.986
RMSE	0.776	0.824	0.666	0.650
Res. Dfs	14,876	15,227	14,772	15,064
	Spatial-regimes AR(1) process: $\alpha_i = D_i \cdot \widehat{A}_R$			
Av. AR(1) coeff.	0.808	0.937	0.812	0.946
Min. AR(1) coeff.	0.613 (type 9)	0.927 (type 9)	0.670 (type 3)	0.916 (type 2)
Max. AR(1) coeff.	0.984 (type 1)	0.949 (type 5)	0.934 (type 1)	0.960 (type 9)
No. of AR(1) >= 1	0/9	0/9	0/9	0/9
No. of AR(1) < 1 (ADF, 5% sign.)	8/9	9/9	9/9	9/9
Av. residuals MI	0.485	0.476	0.425	0.417
Min. residuals MI	0.195	0.198	0.167	0.178
Max residuals MI	0.769	0.746	0.747	0.729
R^2	0.978	0.975	0.981	0.979
RMSE	0.810	0.869	0.754	0.798
Res. dfs	14,914	15,306	14,890	15,291

In terms of the spatial autocorrelation observed in the AR(1) coefficients resulting from Equations (6) and (7), Figure 8 confirms the similarities with the spatial distribution of population density. The spatial distribution of the estimated FE and SF (plotted in Figure 9) again is consistent pairwise, showing higher unexplained variation in the levels for East German districts. Not surprisingly, the light-shaded areas of Figure 8 appear to match the dark-shaded areas of Figure 9, as greater instability in the East German unemployment rates (or just lower dependence from their one-quarter lag) due to unobserved regional characteristics is reflected in the FE or in the SF. Similar observations can be made by comparing Figure 5 and 6, or the two maps in Figure 7.



(a) (b)

Figure 8. Quantile maps of estimated Spatial filter AR(1) coefficients: FE (a) and SF(b) approaches



(a) (b)

Figure 9. Quantile maps of the FE (a) and SF (b) computed for the spatial filter AR(1) process

As a final analysis, we present, in the bottom panels of Table 3, summary statistics for the spatial regimes specification introduced in Equations (8) and (9). In these specifications, heterogeneity of the autoregressive coefficients is introduced by distinguishing between districts with different levels of agglomeration and urbanization. Consequently, instead of N AR(1) coefficients, only nine are computed, corresponding to the specific classes introduced in Section 2.4. This approach makes identification of (average) autoregressive (and seasonal) effects possible for classes such as city-districts in agglomerated areas, or rural districts belonging to rural areas. The results obtained by applying the spatial regimes decomposition to the AR(1) process alone are shown in the bottom-left panel of Table 3. We obtain nine AR(1) coefficients ranging from 0.613 to 0.984 in the FE case, and from 0.927 to 0.949 in the SF case. Consistent with our previous findings (see Table 2), while the average AR coefficients are higher for the SF approach, when employing ADF tests only the FE case presents a unit root. This single unit root (which is not confirmed when decomposing seasonal effects as well) is found for districts of type 1 (that is, 'central cities in regions with urban agglomerations'). This result confirms the tendency of the AR(1) coefficients to resemble the spatial distribution of population density, and of the central business districts (CBDs) of dense regions to show the highest coefficients.

5. Conclusions

Studies about the convergence or persistence of unemployment typically employ univariate autoregressive equations and test them for stationarity. This procedure is straightforward and computationally simple, but can hardly account for cross-sectional heterogeneity and dependence – thus, in the best case, it is statistically inefficient (imprecise) or, in the worse case, mispecified. Derived conclusions may be misleading.

In this paper, we focus on two questions. First, starting with a system of AR(1) equations, we aim to show the substitutability of fixed effects (FE) and spatial filters and, analogously for autoregressive processes, the one between individual autoregressive parameters and SF GWR-type estimation. The SF surrogates are more parsimonious with regard to the number of parameters, and use, instead of region-specific coefficients, a set of coefficients defined and computed over all regions.

Second, we apply SF methods when analysing the dynamics of quarterly regional unemployment rates for Germany from 1996 to 2004. Because the eigenvectors employed in an SF represent map patterns, one advantage of this approach is that the heterogeneous autoregressive adjustment parameters of the GWR-type models have a geographical interpretation. For comparison, we also provide estimates of a homogenous autoregressive process, and of one differentiated according to nine urbanization/agglomeration regimes.

Indeed, when comparing pairwise the individual and SF specifications for process component (AR or level), keeping everything else equal, we find that the SF approach provides a gain in residual degrees of freedom, without loosing much estimation accuracy, measured, for example, in terms of goodness-of-fit (R^2) or root mean squared error (RMSE). We find, for the SF AR specification, some gain in precision when compared with the homogenous and spatial regime specifications. The residual variance and the number of parameters can be combined to compute an information criteria. The Akaike information criterion (AIC) suggests that the SF GWR specification for the autoregressive process uses the information best, when compared to other model specifications. It suggests that FE in the levels are superior to the SF. However, the AIC often is considered insufficient for finite samples, and that other criteria are more reliable. The Schwartz Bayesian information criterion (BIC), which is often found to be over-selective, indicates superiority of the SF in the levels compared to the FE, and superiority of the SF AR process as well, because of the greater importance given to the degrees of freedom saved. An advantage of spatial filters in modelling both levels and autoregressive processes is confirmed by the Hannan-Quinn information criterion (HQ). The residuals from individually-specified models and of their corresponding SF equivalents are highly correlated, and the error distributions are quite similar pairwise. The estimates for the average autoregressive coefficient vary, in particular, between the FE estimation with homogeneous seasonal effects (0.76–0.85) and the remaining level/seasonality combinations (0.90–0.96). Consequently, a potential bias in the autoregressive parameter does not seem to depend on the way in which the autoregressive process is specified. However, obtaining exact evidence about the consistency of the AR estimates is only possible by means of Monte Carlo simulation. This aspect will be the subject of future research, because here we limit ourselves to showcasing the practical relevance of the proposed approaches.

We find the adjustment speed of regional unemployment to shocks to be extremely heterogeneous, which makes estimation of a single AR-coefficient look unreasonable. Modelling the heterogeneity by SF-GWR seems to capture most of this heterogeneity; but, spatial regimes do surprisingly well, too. The average AR coefficient (and the majority of them), throughout the various specifications, lies between 0.76 and 0.96; that is, it is close to

1. Thus, shocks to unemployment are persistent, or have at least a long half-life in most regions: for example, an AR coefficient of 0.8 is equivalent to a half-life of more than three quarters, or the effect of the shock vanishing after eight years (ten times the half-life); an AR coefficient of 0.9 corresponds to a half-life of 6.6 quarters, and a coefficient of 0.95 to a half-life of 13.5 quarters. When using Dickey-Fuller equivalent transformations of the models, we can reject the hypothesis that the difference of the average autoregressive coefficient minus one – the average of this distance is between –0.24 and –0.04 – is greater than or equal to zero. At least on average, unemployment is stationary – a necessary condition for the existence of (conditional) convergence – although non-stationarity can hardly be rejected for a large fraction of regions. Thus, unemployment adjusts very slowly – if ever – toward a kind of natural rate; it behaves (in particular in the agglomerated districts along the river Rhine) more like a random walk, and saying that there is convergence among the rates would be a strong statement. Perhaps, the current pattern – high unemployment in the East, moderate unemployment in the North, and low unemployment in the South – will revert back to its original pattern; nonetheless, such a reversion process would take a long time, and that the effects of the current situation would endure for up to our generation's working life.

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