Heterogeneity and Spatial Dependence of Regional Growth in the EU: A Recursive Partitioning Approach

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Abstract

We use model-based recursive partitioning to assess heterogeneity of growth and convergence processes based on economic growth regressions for 255 European Union NUTS2 regions from 1995 to 2005. Spatial dependencies are taken into account by augmenting the model-based regression tree with a spatial lag. The starting point of the analysis is a human-capital-augmented Solow-type growth equation similar in spirit to Mankiw, Romer, and Weil (1992). Initial GDP and the share of highly educated in the working age population are found to be important for explaining economic growth, whereas the investment share in physical capital is only significant for coastal regions in the PIIGS countries. For all considered spatial weight matrices recursive partitioning leads to a regression tree with four terminal nodes with partitioning according to (i) capital regions, (ii) non-capital regions in or outside the so-called PIIGS countries and (iii) inside the respective PIIGS regions furthermore between coastal and non-coastal regions. The choice of the spatial weight matrix clearly influences the spatial lag parameter while the estimated slope parameters are very robust to it. This indicates that accounting for heterogeneity is an important aspect of modeling regional economic growth and convergence.

Keywords: convergence, growth regressions, recursive partitioning, regional data, spatial dependence.
JEL classification: C31, C51, O18, O47.

1. Introduction

The econometric analysis of the determinants of economic growth and of potential convergence of output across countries or regions has been a major research topic in economics in the last decades. Early empirical contributions include Baumol (1986), Barro (1991) or Barro and Sala-i-Martin (1992). Since then in numerous studies – that employ a broad

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variety of methods – a large number of potential explanatory variables has been considered, for an overview see Durlauf, Johnson, and Temple (2005).

Given the open-endedness of economic growth theories, in the words of Brock and Durlauf (2001), a key question is to determine, out of an often large set of candidates, the variables relevant for economic growth. To address this uncertainty many contributions have applied some form of model averaging, be it Bayesian (e.g., Doppelhofer, Crespo Cuaresma, and Feldkircher 2014; Fernandez, Ley, and Steel 2001) pseudo-Bayesian (e.g., Sala-i-Martin, Doppelhofer, and Miller 2004) or frequentist (e.g., Hlouskova and Wagner 2013; Wagner and Hlouskova 2015). The latter two papers combine model averaging techniques with principal components augmentation to achieve regularization and complexity reduction. Schneider and Wagner (2012) use the adaptive LASSO estimator, that simultaneously performs model selection and parameter estimation, to single out the determinants of economic growth in the regions of the European Union (EU).

The theoretical and empirical growth literatures have put quite some attention on spatial dependencies.[1] In many empirical growth studies spatial dependencies are modeled by including a spatial lag of GDP growth as explanatory variable, with an 'early list' included in Fingleton and Lopez-Bazo (2006). It is perhaps not surprising that many of the studies listed there use regional data as one can expect spatial effects to be more prominent with data at a finer spatial disaggregation, e.g., regions compared to countries. Given this well-documented importance of spatial effects in regional growth studies we also include a spatial lag in our specification to capture spatial dependencies.[2] The spatial setting we consider is inspired by Crespo Cuaresma and Feldkircher (2013), and we use the same regional data set and spatial weight matrices.

All the mentioned contributions assume, however, that the relationship between economic growth and the explanatory variables is identical for all considered countries or regions. This assumption is clearly restrictive given the large theoretical literature implying that growth processes across countries or regions are not necessarily governed by a common (linear or log-linearized) relationship, compare Azariadis and Drazen (1990); Durlauf (1993) and Murphy, Shleifer, and Vishny (1989). These models highlight different mechanisms that may lead to potential nonlinearities in growth processes, e.g., poverty traps or convergence clubs. Furthermore, the usually considered data sets that comprise very heterogeneous countries or regions make the assumption of a common growth process, even when controlling for a variety of variables, at least worth investigating.

The present paper assesses the homogeneity of the growth process by using model-based recursive partitioning for a data set covering the 255 NUTS2 regions of the EU from 1995 to 2005. The approach draws on the rich economic growth literature in two ways: First, a standard and economically interpretable regression model is selected using a human-

[1] Growth models have been extended to incorporate spatial dependencies, e.g., by Egger and Pfaffermayr (2006), Fingleton and Lopez-Bazo (2006) or Fischer (2011). A survey is provided by the handbook chapter of Le Gallo and Fingleton (2014). For an introduction to spatial econometric analysis see, e.g., LeSage and Pace (2009).

[2] We are grateful to the reviewers for insisting on accounting for spatial dependencies in our analysis.

capital-augmented Solow-type growth equation similar in spirit to Mankiw *et al.* (1992). Second, the regression is assessed and split recursively along variables that have previously been employed in studies of potential heterogeneities and nonlinearities of growth and convergence phenomena (especially in the EU). Recursive partitioning of growth regressions to uncover multiple regimes has been considered previously by Durlauf and Johnson (1995). They employ a recursive partitioning algorithm that combines the classification and regression tree (CART) approach of Breiman, Friedman, Olshen, and Stone (1984) with residual sums of squares from growth regressions. While that approach lacks a concept of (asymptotic) significance of the regimes found, we use a modern model-based extension of the classic recursive partitioning approach suggested by Zeileis, Hothorn, and Hornik (2008) based on formal (score-based) parameter stability tests. Moreover, to account for spatial autocorrelation, their approach is enhanced by including a spatial lag, employing an iterative technique inspired by Sela and Simonoff (2012) and Hajjem, Bellavance, and Larocque (2011).

The spatial regression and recursive partitioning methods are presented in Section 2 before Section 3 introduces the details of the data and variables considered. The results of the analysis are discussed in Section 4 and Section 5 concludes. The appendix contains the results for the model tree without spatial dependence along with further supplementary figures. The method used in this paper is available as the R package **lagsarlmtree** from R-Forge (Wagner and Zeileis 2017), including replication material for the paper.

2. Method

2.1. Heterogeneous Growth Regression with Spatial Lag

As will be discussed and motivated in more detail in Section 3, the growth regression considered as a starting point for our analyses is a human-capital-augmented Solow-type model:

$$\begin{aligned} y_i &= \beta_0 + x_{i1}\beta_1 + \dots + x_{i4}\beta_4 + \varepsilon_i \\ &= x_{i\bullet}^\top \beta + \varepsilon_i, \end{aligned} \tag{1}$$

for our sample of $i = 1, \dots, 255$ EU regions with the dependent variable $y = (y_1, \dots, y_n)^\top$, the annual growth rate of real GDP per capita over 1995–2005 ('ggdpcap'), $x_1 = (x_{11}, \dots, x_{n1})^\top$ the logarithm of initial GDP in 1995 ('gdpcap0'), $x_2 = (x_{12}, \dots, x_{n2})^\top$ the share of gross fixed capital formation ('shgfcf'), $x_3 = (x_{13}, \dots, x_{n3})^\top$ and $x_4 = (x_{14}, \dots, x_{n4})^\top$ the shares of highly and medium educated population ('shsh' and 'shsm'). As usual, $\varepsilon = (\varepsilon_1, \dots, \varepsilon_n)^\top$ denotes the error vector.

The 'standard' specification (1) is extended in two directions: First, to capture spatial dependencies a spatial lag of the dependent variable is added to the model. Second, the parameter vector β is not assumed to be stable over all 255 observations but allowed to vary across 'groups of regions'. The groups are determined from additional 'partitioning' variables using model-based trees (also known as model-based recursive partitioning, Zeileis *et al.* 2008). Thus, the extended heterogeneous growth regression with spatial lag is given by:

$$y_i \quad = \quad \rho w_i^\top y + x_{i\bullet}^\top \beta^{g(i)} + \varepsilon_i, \tag{2}$$

where w_i is the vector of spatial weights for the i-th observation, ρ is the spatial lag parameter, and $\beta^{g(i)}$ is the parameter vector in the group $g(i)$ to which observation i belongs. The group $g(i)$ for the i-th observation is found by performing recursive splits in 'partitioning' variables. It is important to note that we allow with this specification for a 'global' spatial lag parameter ρ, that multiplies the individual specific spatially lagged observation $w_i^\top y$, and group-specific coefficients $\beta^{g(i)}$ for the explanatory variables. In our empirical analysis we employ the same set of spatial weight matrices as Crespo Cuaresma and Feldkircher (2013). As already alluded to above, the results are surprisingly robust with respect to the choice of the weighting matrix. This is discussed in more detail in Section 4.

2.2. Estimation: Spatial Dependence and Group Structure

Estimating the parameters in (2) is not a straightforward task. It is well understood in the literature how to estimate ρ in a situation without group-specific coefficients or with given groups. But simultaneously determining an unknown grouping and estimating the spatial lag coefficient is challenging. The problem is analogous to problems faced when estimating panel data models with group structure and individual (fixed) effects that can be correlated with groups of observations. A simple iterative method to tackle this problem is proposed in Sela and Simonoff (2012) and Hajjem *et al.* (2011). We adapt their approach to our situation, with a spatial lag rather than an individual effects structure.

The estimation procedure iterates between estimating the parameter ρ for given group structure (i.e., given regression tree) and estimation of the group structure for given spatial lag parameter. More precisely, the following two steps are iterated until convergence, i.e., until the regression tree does not change:

1. Given the groups $g(i) \in \{1, \ldots, G\}$ for all observations i, the model in (2) is a standard spatial lag model (with interactions between groups and regressors) and can thus be estimated, e.g., by maximum likelihood as discussed from a computational perspective in Bivand and Piras (2015). This yields both $\hat{\rho}$ and $\hat{\beta}^g$ for $g = 1, \ldots, G$.

2. Given an estimate of the spatial lag parameter $\hat{\rho}$, the dependent variable can be adjusted for the spatial dependence, i.e., $\tilde{y}_i = y_i - \hat{\rho} w_i^\top y$ can be constructed. Then a standard linear regression tree approach (Zeileis *et al.* 2008) can be used to estimate the parameters $\beta^{g(i)}$ in

$$\tilde{y}_i = x_{i\bullet}^\top \beta^{g(i)} + \varepsilon_i \tag{3}$$

   and to perform recursive partitioning (as described in the following subsection). This yields an estimate of the group $g(i)$ for each observation i.

The described iterative procedure can be initialized in either step: in the first step with all observations in a single group or in the second step without spatial dependence, i.e., with $\rho = 0$ and standard recursive partitioning. In our analysis the results do not depend upon the starting point of the iteration and we need only one iteration step to reach convergence.

2.3. Estimation: Model-Based Trees

The second step of the estimation algorithm above relies on the estimation of a linear regression tree as discussed in Zeileis *et al.* (2008) that determines the group structure. This iterates between (a) estimating the parameters of (3) in the given (sub)sample by ordinary least squares (OLS) and (b) in case of evidence for non-stable β-coefficients splitting the considered sample into two subsamples. For step (b) additional 'partitioning' variables are employed with respect to which parameter stability is first assessed and, if any is found, the best split in subsamples is selected by minimizing the residual sum of squares of the partitioned model.

The parameter instability tests considered have first been suggested in the context of time series regressions but can also be applied to other contexts (e.g., Hjort and Koning 2002; Zeileis and Hothorn 2013). More specifically, the stability of the regression coefficients is tested using the supLM test of Andrews (1993) for numerical partitioning variables:

$$\sup LM \quad = \quad \sup_{i=\underline{i},\dots,\overline{\imath}} \left\{ \frac{i}{n} \left(1 - \frac{i}{n}\right) \right\}^{-1} \left|\left| \hat{V}^{-1/2} n^{-1/2} \sum_{\ell: z_\ell \leq z_{(i)}} x_{\ell\bullet} \hat{\varepsilon}_\ell \right|\right|_2^2, \tag{4}$$

where z_i denotes observation i of the considered partitioning variable, after ordering according to increasing size denoted by $z_{(i)}$. Furthermore, $\hat{\varepsilon}$ is the vector of OLS residuals; based on parameter estimation on the considered (sub)sample. $\hat{V} = n^{-1} \sum_{i=1}^n \hat{\varepsilon}_i^2 x_{i\bullet} x_{i\bullet}^\top$ is the outer-product-of-gradients (OPG) covariance estimate, employed to normalize the sums of the score vectors $x_{i\bullet}\hat{\varepsilon}_i$.

For categorical partitioning variables the test statistic is given by:

$$\chi^2 \quad = \quad \sum_{c=1,\dots,C} \left|\left| \hat{V}^{-1/2} n_c^{-1/2} \sum_{i: z_i = c} x_{i\bullet} \hat{\varepsilon}_i \right|\right|_2^2, \tag{5}$$

denoting here with $c = 1, \dots, C$ the categories of the partitioning variable z and with n_c the number of observations of z in category c.

Asymptotic p-values for both tests can be computed from the corresponding limiting distributions: supremum of a squared tied-down Bessel process for the sup LM-test (see Hansen 1997) and chi-squared with $5 \times (C - 1)$ degrees of freedom for the χ^2-test, respectively. See Hjort and Koning (2002) and Zeileis (2005) for a unifying view and further discussions of these parameter stability tests. Additionally, we apply a Bonferroni-type correction to the p-values to correct for testing along several (and not just a single) partitioning variable.

The recursive partitioning procedure stops if no more significant instabilities are detected (at the 5% level) or the subsample becomes too small (less than twelve observations in our application). In each of the resulting subsamples or 'groups of regions' the basic Solow-type model above is fitted. Consequently, we model growth and convergence for EU regions as linear, but with different coefficients for different 'groups of regions'.[3]

3. Data

The data used in this paper are a subset of the variables used in Schneider and Wagner (2012), see Table 1 for a list of variables.[4] The regional dataset covers the 255 NUTS2 regions in the 27 member countries (at the end of the sample period) of the EU over the period 1995–2005. The selection of variables used here from the larger dataset available is based on the following considerations. First, as already discussed above, the basis of our model-based recursive partitioning approach is a simple, economically interpretable relationship. Second, as partitioning variables we consider variables according to which partitioning and heterogeneity appears to be a potential issue, given growth theory, the institutional and historical characteristics present in the EU, and the available empirical evidence. Third, the number of partitioning variables is limited by the need for having a sufficient set of observations in each (terminal) node. Fourth, we build in the analysis on the findings of Schneider and Wagner (2012) and Wagner and Hlouskova (2015) who use the same data.

The dependent variable y is the average growth rate of real GDP per capita (ggdpcap) and the regressors are initial real GDP per capita in logs (gdpcap0, x_1), sometimes simply referred to as initial income, to capture potential β-convergence; the investment share in GDP (shgfcf, x_2) to capture physical capital accumulation and the shares of high and of medium educated in the labor force (shsh and shsm, x_3 and x_4) as measures of human capital. Thus, in effect we estimate a human-capital-augmented version of the Solow model, inspired by the by now classical work of Mankiw *et al.* (1992).[5]

We employ the following partitioning variables:

- First, we use the log of initial real GDP per capita itself as a partitioning variable as a simple device to check for the presence of initial income driven convergence clubs. The important role of initial real GDP per capita in shaping growth and convergence dynamics in the form of, e.g., convergence clubs has been documented in many papers dealing with EU regions including Azomahou, El Ouardighi, Nguyen-Van, and Pham (2011), Basile (2008), Firgo and Huber (2014), Fotopoulos (2012), or Petrakos, Kallioras, and Anagnostou (2011).

[3] Note that this strategy bears some resemblance to the approach of Crespo Cuaresma, Foster, and Stehrer (2011). However, whilst they 'partition' according to quantiles of the distribution of the *dependent* variable, our partitioning is related to a set of partitioning variables.

[4] Schneider and Wagner (2012, Table 3) and Fingleton and Lopez-Bazo (2006, Table 1) list empirical studies on growth and convergence of EU regions, with the latter focusing on spatial dependencies.

[5] Furthermore, note that Crespo Cuaresma and Feldkircher (2013) only find three variables with posterior inclusion probabilities larger than 0.5: these are initial income, the capital dummy and the share of high educated in the labor force. These three are included in our set.

Type		Name	Description
Dependent	y	ggdpcap	Average annual growth rate of real GDP per capita over the period 1995–2005 (Eurostat)
Regressor	x_1	gdpcap0	Real GDP per capita in logs in 1995 (Eurostat)
	x_2	shgfcf	Share of gross fixed capital formation in gross value added (Cambridge Econometrics)
	x_3	shsh	Share of highly educated in working age population (Eurostat)
	x_4	shsm	Share of medium educated in working age population (Eurostat)
Partitioning		accessrail	Measure for potential accessability by rail (ESPON)
		accessroad	Measure for potential accessability by road (ESPON)
		capital	Dummy variable for the 27 capital regions (ESPON)
		regborder	Dummy variable for the 136 border regions (ESPON)
		regcoast	Dummy variable for the 118 coastal regions (ESPON)
		regobj1	Dummy variable for the 104 Objective 1 regions eligible for EU structural funds (ESPON)
		cee	Dummy variable for the 53 regions in the Central and Eastern European countries
		piigs	Dummy variable for the 57 regions in Portugal, Ireland, Italy, Greece and Spain

Table 1: List of variables including sources. Note that the variable gdpcap0 is used both as regressor and partitioning variable.

- We use two measures for traffic accessibility of the region, one for accessibility via rail (accessrail) and one via the road network (accessroad). Clearly, integration in the European traffic networks is beneficial for trade and thus for economic development and growth. This variable has been found important, e.g., in Sanso-Navarro and Vera-Cabello (2015).

- A dummy variable for capital regions (capital) is used. This variable has been found significant in Schneider and Wagner (2012) and has posterior inclusion probability equal to one in Crespo Cuaresma and Feldkircher (2013), in line with the large literature on core-periphery effects in new economic geography models (compare Fujita, Krugman, and Venables 1999). For additional empirical evidence highlighting the importance of agglomeration effects in the EU see, e.g., Geppert and Stephan (2008).

- We also consider dummy variables for border regions (regborder) and coastal regions (regcoast). Both of these variables are related to trade (and its impact on economic growth). Since the seminal study of McCallum (1995) that has investigated the detrimental effect of national borders on trade in North America border effects have been found important in many empirical trade studies. Matters are ex ante less clear with respect to coastal regions since these are faced on the one hand with a 'border' with the sea but are for exactly that reason on the other hand (at least partly) the locations of ports. From this perspective coastal regions are expected to benefit from both EU imports and exports as well as from infrastructure investments.

- A key tool of EU policy is to foster regional development via its structural funds, with the prime recipients of such funds being the so-called Objective 1 regions (regobj1). We include the corresponding dummy variable to assess the potential effects of EU structural funds on the regional growth performance (compare also Lall and Yilmaz 2001).

- Additionally we include two dummy variables corresponding to two different groups of countries. One is a CEE dummy for ten Central and Eastern European countries (i.e., Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Romania, Slovak Republic, and Slovenia) and the other is for the so-called PIIGS countries (Portugal, Ireland, Italy, Greece, and Spain). The former group comprises previously centrally planned economies that have joined the EU at the very end (May 1, 2004) or even after the sample period (January 1, 2007 in case of Bulgaria and Romania). Against this background (central planning legacy, recent EU membership) it sounds reasonable to at least check whether the regions in these countries have experienced a different growth performance over our sample period. Details concerning the specificities of the growth process of these countries as well as growth projections are contained in Wagner and Hlouskova (2005). The PIIGS group comprises Southern or Western peripheral countries that have experienced a substantial crisis in the aftermath of the global financial crisis. These regions are considered separately in order to see whether their growth performance has been different already prior to the crisis. The differential growth and convergence performance of the PIIGS countries already prior to the crisis is, e.g., documented in Ertur, Le Gallo, and Baumont (2006).

- In our calculations we use 24 of the spatial weight matrices of Crespo Cuaresma and Feldkircher (2013), including matrices based on nearest neighbors, distance bands, and exponential decay (inverse distance).[6] Given the remarkable robustness of our result with respect to the weight matrix chosen we focus in the following section on the results obtained with the standard inverse distance weight matrix and only comment upon the differences obtained with other weight matrices.[7]

[6]To be precise we initially used all spatial weight matrices of Crespo Cuaresma and Feldkircher (2013). However, for Queen matrices and low distance bands this leads to a number of observations without neighbors, namely in coastal regions in Cyprus, Greece, Italy, and Malta. Excluding those observations leads to qualitatively similar results but for some weight specifications the coastal PIIGS regions are not significantly different (due to the reduced number of such regions).

[7]The robustness with respect to the specification of the spatial weight matrix is not a given, see the discussion in Fingleton and Lopez-Bazo (2006, p. 179) and potentially indicates that the partitioning into different groups robustifies findings against the effects of misspecifying the weight matrix. This is an issue that needs to be investigated in detail in future research.

4. Results

As just mentioned, the results in this section are based on the inverse distance weight matrix, with the results for the specification without spatial lag presented as a benchmark in the appendix. The spatial lag parameter for the inverse distance weight matrix is estimated at $\hat{\rho} = 0.837$ and is highly significant. The high value of the spatial lag parameter depends on the chosen weight matrix and is lower for most other matrices (with an average of 0.357). However, changing the weight matrix exhibits such strong effects only on the lag parameter but has mainly only minor effects on the estimated slope coefficients, as illustrated in Figure 1, and does not affect the tree structure, as shown in Figure 2.

Throughout, for all four groups (terminal nodes) and for all coefficients, the box plots describing the 24 point estimates obtained using the different weight matrices are very narrow and the variation due to the weight matrices is much smaller than the variation of the coefficients across groups. The coefficients to the different variables are sizeably different across groups and are partly of different sign across groups. In this sense accounting for heterogeneity by recursive partitioning is more important than the (specific choice of) spatial weights. Accounting for spatial dependencies does have an effect on the estimated coefficients, as can be seen by comparing the spatial results with the regression true estimates without spatial lag (the triangles in the graphs). The point estimates obtained without accounting for spatial dependencies differ from the spatial estimates, but again

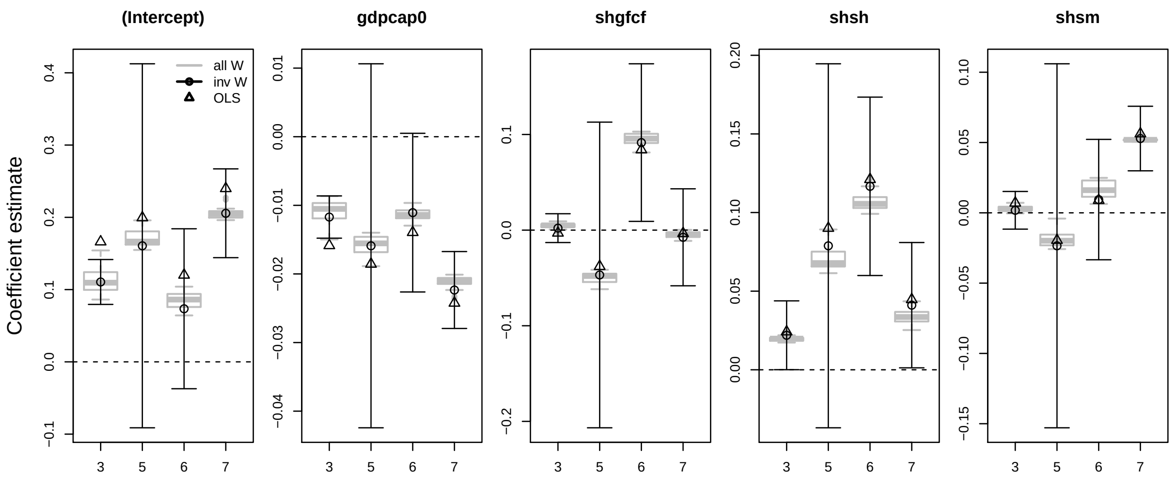

Figure 1: The panels summarize the coefficient estimates from the different model specifications for each of the terminal nodes (3, 5, 6 and 7) of the regression tree. The gray box plots capture the 24 point estimates obtained using the different spatial weight matrices. The black circles and lines correspond to the point estimates and 95% confidence intervals using the inverse distance weight matrix. The black triangles correspond to the point estimates from the regression tree without spatial dependence (with the detailed results given in the appendix).

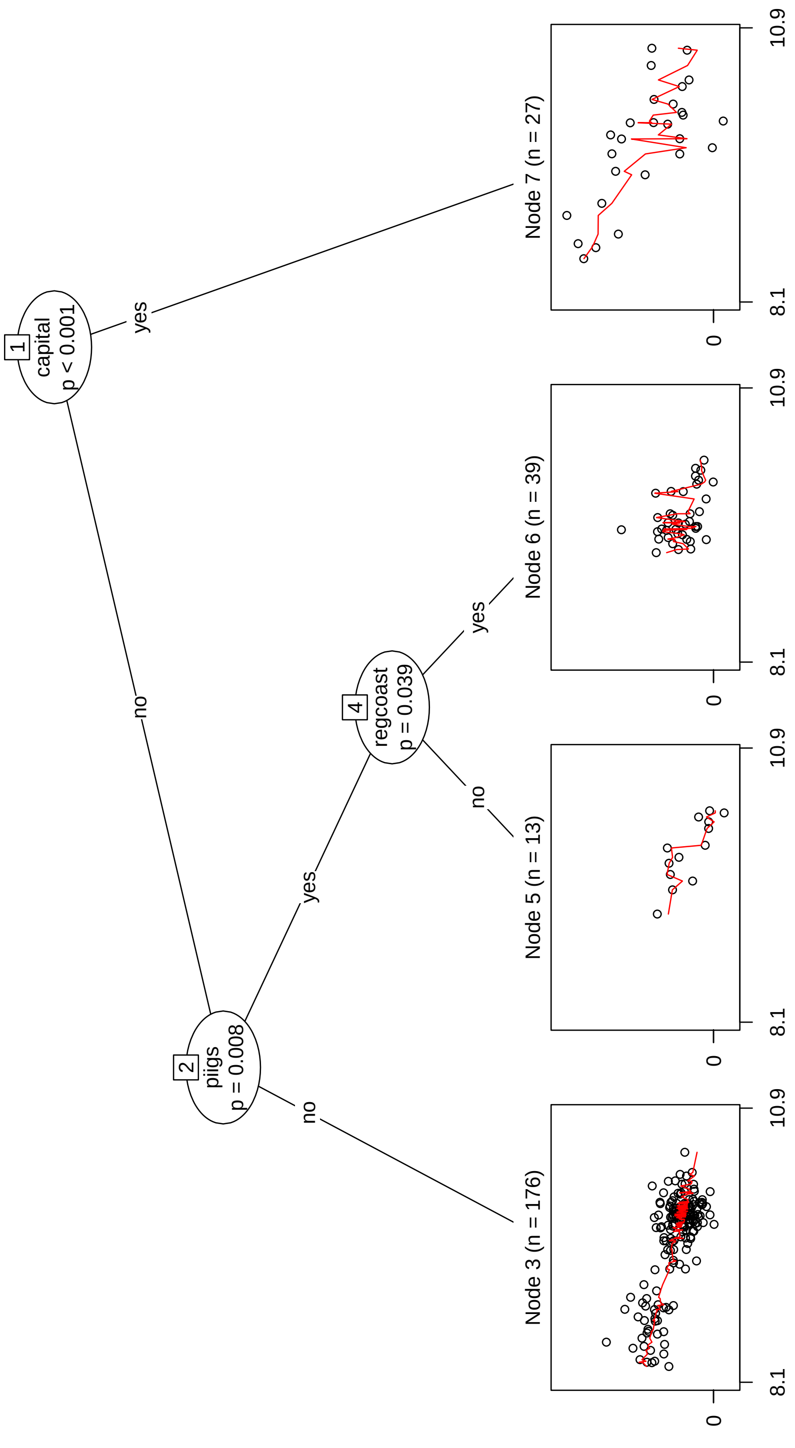

Figure 2: Fitted linear regression tree. In the inner nodes the p-values from the parameter stability tests are displayed and in the terminal nodes a scatter plot of GDP per capita growth (ggdpcap) vs. (log) initial real GDP per capita (ggdcap0) along with fitted values is depicted.

	gdpcap0 (num)	accessrail (num)	accessroad (num)	capital (bin)	regborder (bin)	regcoast (bin)	regobj1 (bin)	cee (bin)	piigs (bin)
1	22.100	23.389	24.623	67.544	3.884	10.911	6.696	21.698	8.312
	0.114	0.069	0.042	< 0.001	0.999	0.388	0.920	0.005	0.742
2	19.258	17.373	16.051	–	6.461	7.794	4.376	9.099	20.663
	0.278	0.480	0.648	–	0.914	0.770	0.996	0.589	0.008
3	22.154	16.668	13.797	–	8.597	4.477	5.310	7.147	–
	0.088	0.519	0.859	–	0.611	0.990	0.964	0.808	–
4	5.488	9.654	9.697	–	7.987	16.089	3.254	–	–
	1.000	0.981	0.979	–	0.641	0.039	0.998	–	–
5	–	–	–	–	–	–	–	–	–
	–	–	–	–	–	–	–	–	–
6	6.866	5.203	8.431	–	5.604	–	3.465	–	–
	0.998	1.000	0.975	–	0.881	–	0.993	–	–
7	6.676	4.074	3.692	–	1.673	3.586	4.988	9.156	8.034
	0.995	1.000	1.000	–	1.000	0.999	0.987	0.581	0.739

Table 2: Parameter stability tests (test statistic and p-value) for all partitioning variables in each of the tree's nodes in the final iteration of the estimation procedure using the inverse distance weight matrix. For numerical variables (num) the Andrews (1993) supLM test is used and for binary variables (bin) a score-based χ^2 test.

the variation is larger across subgroups. The point estimates obtained with the inverse distance weight matrix are depicted in Figure 1 as black circles together with 95% confidence intervals. The figure shows that the point estimates obtained without spatial lag included are with very few exceptions not significantly different from the estimates based on the inverse distance weight matrix. The largest differences between the two estimates occur for the intercept and initial income, whereas for the other three variables the estimated coefficients are very similar for the specification without spatial lag and the inverse distance weight matrix specification. The drastically different sizes of the confidence intervals across groups essentially reflect the different sample sizes in the different terminal nodes, ranging form 13 observations in node 5 to 176 observations in node 3.

In addition to the discussed minor changes of the numerical values of the estimated coefficients across weight matrices, also the p-values from the parameter stability tests in the nodes of the tree change to a certain degree. While the split with respect to capital regions in the root node is highly significant for all weight specifications, the p-values for the splits in node 2 (PIIGS regions) and node 4 (coastal regions) increase in some specifications but always remain significant at the 10% significance level. The p-values for all weight specifications are shown in Figure 4 in the appendix.

Let us now focus on the results obtained with the inverse distance weight matrix in more detail. The corresponding results for the parameter stability tests in the final iteration of the estimation procedure are shown in Table 2. There are three splits at the 5% significance level. First, according to the capital dummy, second with respect to the PIIGS dummy and third with respect to being a coastal region within the PIIGS countries. This leads to the discussed tree with four terminal nodes, see also the visualization in Figure 2. Note, however, that in the first block-row of Table 2 also for two more variables the null hypothesis of parameter stability is rejected at the 5% level (with p-values higher than that of capital). These are the road accessibility measure and the CEE dummy. Thus, viewed in isolation there is indeed evidence for heterogeneity along these variables. Nevertheless, after partitioning according to the capital region dummy, neither of the two variables reappears as a variable indicating associated heterogeneity. E.g., the finding with respect to the CEE dummy, not being significant as partitioning variable after partitioning according to the capital region dummy, is in line with the fact that for many of the CEE countries the bulk of growth has occurred in the capital region.

As initial income is not selected as a partitioning variable, it appears that there is no evidence for initial income driven convergence clubs. However, when considering the terminal node of the 176 non-capital non-PIIGS regions there is evidence for parameter instability with respect to initial income at the 10% significance level for some weight matrices (see Figure 4 in the appendix). This can also be seen in the lower left graph of Figure 2, where a 'blurred' separation in two clusters grouped according to initial income is visible.[8]

Analogously, since the border dummy is not selected as a partitioning variable, there is no strong evidence for border effects impacting the growth performance in the EU. This result is to a certain extent surprising as the Central Eastern European countries have (essentially) not been members of the EU in the sample period considered. It also appears that being an Objective 1 region does not lead to a differential growth process, which is in line with some of the literature that finds hardly any growth promoting effect of EU structural funds; for an early assessment see Canova and Marcet (1997).

Altogether, the splits are informative and in line with our discussion in Section 3 highlighting potentially important mechanism for growth heterogeneity. The fact that the first split is in capital and non-capital regions forcefully stresses the importance of agglomeration externalities discussed in the previous section. The differential growth performance of the PIIGS countries already prior to the financial crisis documented in Ertur *et al.* (2006) is discovered also by our recursive partitioning approach with the PIIGS dummy variable being the second split variable, with the PIIGS regions then furthermore split into coastal and non-coastal regions.

Let us finally turn to the regression results obtained for the inverse distance weight matrix given in Table 3. The results for the specification without spatial lag are given in the appendix in Table 5 for comparison and as benchmark. The results in the appendix are both quantitatively and qualitatively very similar, as has already become clear from the discussion. The tables show the results for the four terminal nodes shown also in Figures 2 and 3 in the appendix respectively. For comparison we also display the corresponding results of Crespo Cuaresma and Feldkircher (2013) and Schneider and Wagner (2012).

[8] If one were to enforce a split according to the logarithm of initial real GDP per capita, the split point is 9.249. The estimation results between the corresponding two subsets differ in that only in the high initial income regions the share of highly educated in the labor force is significant with positive effect.

	n	Partitioning variables			Regressor variables				
		capital	piigs	regcoast	(Const.)	gdpcap0	shgfcf	shsh	shsm
3	176	no	no	–	0.111	−0.0117	−0.0021	0.022	0.0018
					(0.016)	(0.0016)	(0.0077)	(0.011)	(0.0068)
5	13	no	yes	no	0.161	−0.0159	−0.0469	0.079	−0.0234
					(0.128)	(0.0135)	(0.0815)	(0.059)	(0.0660)
6	39	no	yes	yes	0.073	−0.0111	0.0916	0.117	0.0094
					(0.056)	(0.0059)	(0.0420)	(0.029)	(0.0218)
7	27	yes	–	–	0.206	−0.0223	−0.0075	0.041	0.0528
					(0.031)	(0.0029)	(0.0259)	(0.020)	(0.0117)
Crespo Cuaresma and Feldkircher (2013)						−0.016	0.002	0.037	
						(0.004)	(0.007)	(0.023)	
Schneider and Wagner (2012)					0.1613	−0.0156		0.0602	0.0134
					(0.0105)	(0.0011)		(0.0078)	(0.0038)

Table 3: Estimated results in the final iteration of the regression tree. Number of observations n, the partitioning variables selected, and the estimated slope coefficients (with standard errors in brackets) are provided. The estimated spatial lag parameter is given by $\hat{\rho} = 0.837$ with standard error of 0.105. The row 'Crespo Cuaresma and Feldkircher (2013)' displays the posterior means and posterior standard deviations of the coefficient estimates averaged over all used weight matrices as given in the supplementary material of their paper. The row 'Schneider and Wagner (2012)' displays the LASSO point estimates and their standard deviations obtained in that paper. Empty entries indicate variables for which the results are not available (not displayed or variable not included).

For all four groups the coefficient to initial income is negative, albeit not significant for the group comprising 13 non-coastal non-capital regions in the PIIGS countries.[9] The most negative coefficient and thus the highest speed of conditional β-convergence is observed for the 27 capital regions. For spatial models, Egger and Pfaffermayr (2006) define the implied convergence speed as 'speed of convergence proper' as it does not take into account the feedbacks through the spatial lag effects.[10] The share of gross fixed capital formation is often found not to be significant in the 'homogenous growth' literature, e.g., it is not significant in Crespo Cuaresma and Feldkircher (2013) and not selected by the adaptive LASSO estimator in Schneider and Wagner (2012). For our regression tree model, we find significance of investment for the coastal non-capital regions in the PIIGS countries. The share of highly educated in the labor force is significant in all but the group of 13 non-coastal non-capital PIIGS regions. For this variable again the largest coefficient is observed for the capital regions, in line with agglomeration and hub-effects (headquarters, scientific institutions, etc.) characteristic for the economic structure of capital regions. Our coefficient estimates are, of course, not too different from the coefficient estimates obtained in the two reference studies, with the benefit of highlighting the substantial heterogeneity across groups of regions that allows to zoom in more closely in an economically meaningful

[9] Here, of course, also the small sample size limits the likelihood of obtaining significant coefficients.

[10] Ertur, LeGallo, and LeSage (2007) refer to this parameter as *global convergence* parameter.

way by using partitioning variables that the literature describes as potentially important based on either empirical or theoretical considerations.

5. Summary

The paper demonstrates that the growth process in the 255 NUTS2 regions of the European Union over the period 1995–2005 is characterized by both spatial dependencies and heterogeneity. In order to uncover these results we propose an iterative procedure that allows to combine the inclusion of spatial lags with model-based recursive partitioning.

It turns out that the results are, with few exceptions, very robust across the large number of spatial weight matrices considered. The spatial lag parameter, of course, depends upon the weight matrix chosen. However, with few exceptions for the intercept and partly the coefficient to initial income, the slope coefficients are not strongly affected by the choice of the spatial weight matrix, or the inclusion of a spatial lag altogether. It turns out that for the slope coefficients the variation across the four identified terminal nodes is quantitatively much more important.

The regions are partitioned into (i) capital and non-capital regions; (ii) the non-capital regions are furthermore split between regions inside and outside the PIIGS countries; (iii) the (non-capital) PIIGS regions are split into coastal and non-coastal regions.

For all but the group of 13 non-coastal non-capital regions in the PIIGS countries conditional convergence prevails. The convergence speed is significantly larger for the 27 capital regions than the two other groups where conditional convergence prevails. The share of highly educated in the labor force is also significant for all but the 13 regions mentioned above. The share of gross fixed capital formation in GDP, typically found not to be significant in the literature, is found to be significant in the (non-capital) coastal PIIGS regions. Thus, whilst our findings are in the ballpark of findings obtained with the same or similar data using homogenous specifications, allowing for heterogeneity offers additional informative insights.

Additionally, the paper highlights how model-based recursive partitioning may complement the econometric toolbox of empirical growth researchers: By combining well-established ‘standard’ models (the human-capital-augmented Solow-type equation in our case) with knowledge about further potential factors whose precise effects on economic growth are not clear ex ante, groups and interaction effects can be revealed. While the technique is exploratory in spirit, it is based on formal inference for parameter stability, thus controlling its significance level. Aided by the tree visualization, the results are furthermore straightforward and easy to interpret.

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A. Supplementary Material

	gdpcap0 (num)	accessrail (num)	accessroad (num)	capital (bin)	regborder (bin)	regcoast (bin)	regobj1 (bin)	cee (bin)	piigs (bin)
1	25.467	27.513	29.840	73.495	3.968	13.507	7.189	23.381	10.358
	0.030	0.012	0.004	< 0.001	0.999	0.159	0.876	0.003	0.457
2	21.241	20.087	20.687	–	7.547	9.846	5.075	11.112	19.779
	0.141	0.211	0.171	–	0.802	0.485	0.985	0.332	0.011
3	22.311	22.640	19.480	–	9.248	7.945	6.531	8.247	–
	0.082	0.073	0.229	–	0.520	0.703	0.876	0.661	–
4	6.608	10.155	10.150	–	8.556	17.039	3.076	–	–
	1.000	0.965	0.965	–	0.561	0.027	0.999	–	–
5	–	–	–	–	–	–	–	–	–
	–	–	–	–	–	–	–	–	–
6	7.392	6.452	8.781	–	5.836	–	3.280	–	–
	0.994	0.999	0.963	–	0.857	–	0.995	–	–
7	6.962	3.789	3.425	–	2.040	4.065	4.766	9.389	7.937
	0.991	1.000	1.000	–	1.000	0.998	0.991	0.548	0.752

Table 4: Parameter stability tests (test statistic and p-value) for all partitioning variables in each of the tree's nodes (OLS). For numerical variables (num) the Andrews (1993) supLM test is used and for binary variables (bin) a score-based χ^2 test.

	Summary		Partitioning variables			Regressor variables				
	n	R^2	capital	piigs	regcoast	(Const.)	gdpcap0	shgfcf	shsh	shsm
3	176	0.505	no	no	–	0.166	−0.0159	−0.0030	0.024	0.0070
						(0.013)	(0.0014)	(0.0071)	(0.010)	(0.0063)
5	13	0.923	no	yes	no	0.199	−0.0186	−0.0379	0.090	−0.0195
						(0.067)	(0.0071)	(0.0426)	(0.031)	(0.0345)
6	39	0.560	no	yes	yes	0.120	−0.0139	0.0840	0.121	0.0089
						(0.054)	(0.0056)	(0.0401)	(0.028)	(0.0208)
7	27	0.620	yes	–	–	0.240	−0.0242	−0.0034	0.045	0.0563
						(0.063)	(0.0058)	(0.0527)	(0.041)	(0.0238)

Table 5: Fitted linear regression models (OLS) for terminal nodes in the tree. Summary information (number of observations n and R^2), the partitioning variables selected and regression coefficients (with standard errors in brackets) are provided.

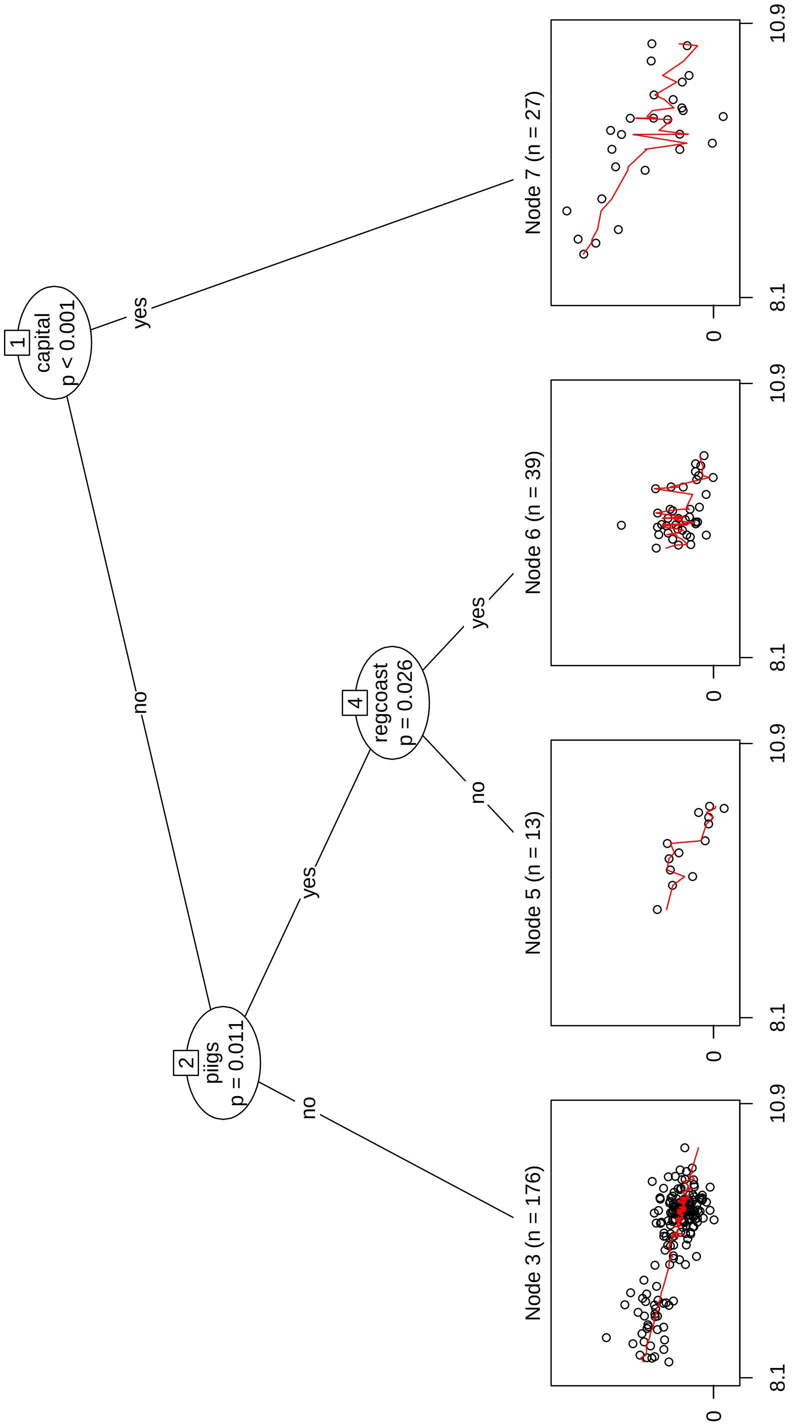

Figure 3: Fitted linear regression tree (OLS). In the inner nodes the *p*-values from the parameter stability tests are displayed and in the terminal nodes a scatter plot of GDP per capita growth (ggdpcap) vs. (log) initial real GDP per capita (ggdcap0) along with fitted values is depicted.

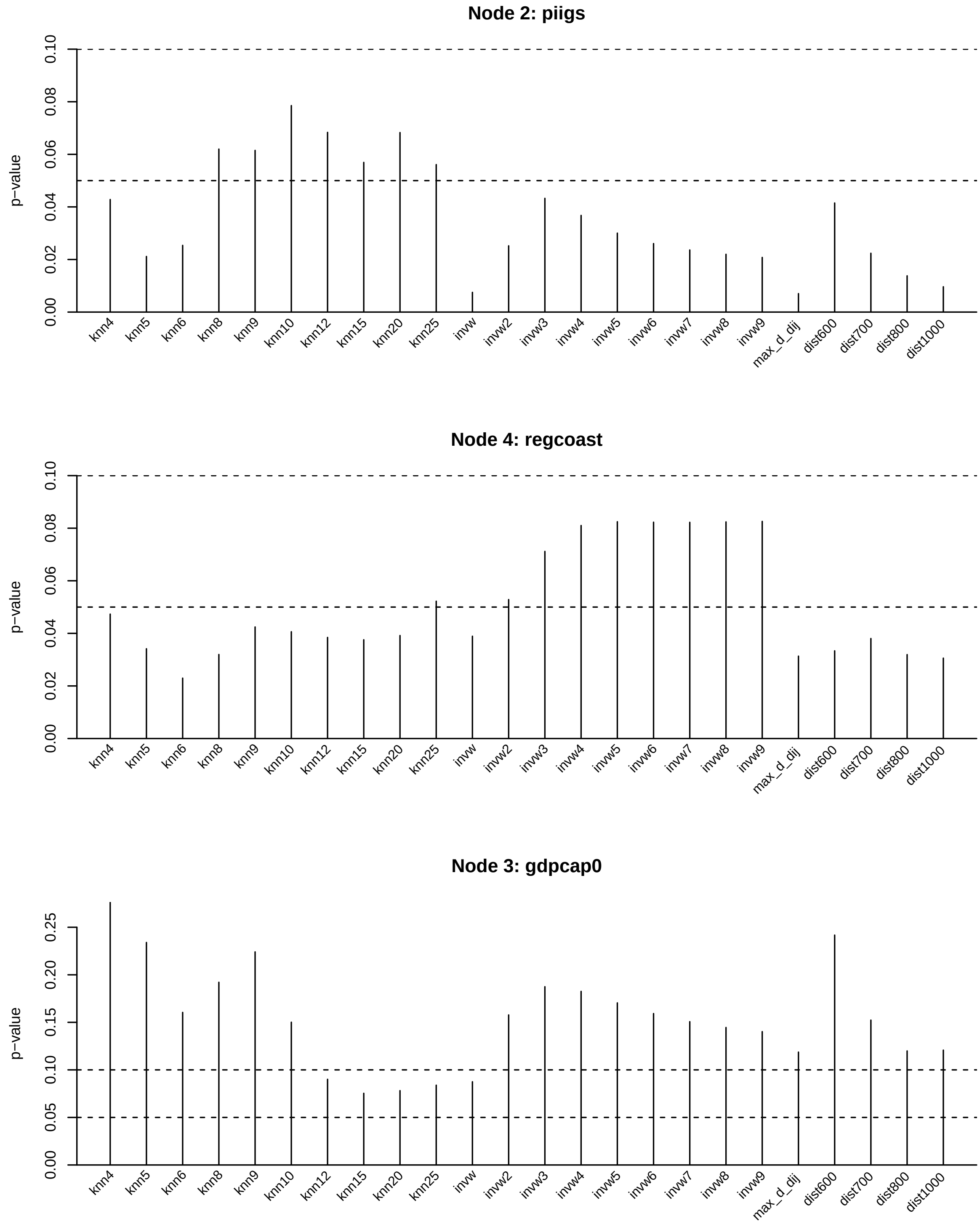

Figure 4: p-values from parameter instability tests (OLS) in node 2 (for variable PIIGS), in node 4 (for coastal region), and node 3 (for initial income, gdpcap0) across all 24 considered spatial weight matrices.

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