WIRTSCHAFTSUNIVERSITÄT WIEN
Vienna University of Economics and Business

Master's Thesis

Title of Master's Thesis:	Regional Growth Determinants Across the European Union and its Candidates
Author (last name, first name):	Di Gregorio Elia
Student ID number:	12039313
Degree program:	Master in Economics
Examiner (degree, first name, last name):	Univ.Prof.Dr. Jesús Crespo Cuaresma

I hereby declare that:

1. I have written this master's thesis myself, independently and without the aid of unfair or unauthorized resources. Whenever content has been taken directly or indirectly from other sources, this has been indicated and the source referenced. I am familiar with the regulations specified in the Directive on Plagiarism and Other Types of Academic Fraud in Academic Theses.

2. This master's thesis has not been previously presented as an examination paper in this or any other form in Austria or abroad*.

3. This master's thesis is identical with the thesis assessed by the examiner.

4. (only applicable if the thesis was written by more than one author): this master's thesis was written together with

The individual contributions of each writer as well as the co-written passages have been indicated.

22.10.2024
Date

Di Gregorio Elia
Signature

*This does not apply to master's theses written as part of WU cooperation programs (joint or double degrees).

Regional Growth Determinants Across the European Union and its Candidates

Vienna University of Business and Economics

Department of Economics

Elia Di Gregorio

Thesis Supervisor: Univ.Prof.Dr. Jesús Crespo Cuaresma

22 October 2024

Abstract

This study examines regional economic growth determinants in 301 European NUTS-2 regions across EU Member States and Candidate countries from 2009 to 2019. Using Bayesian Model Averaging and spatial econometric techniques on 30 variables, it addresses model uncertainty and spatial dependencies. Key findings reveal that human capital and industrial activity drive growth, while reliance on the construction sector hinders it. Evidence supports convergence, with poorer regions growing faster but unevenly, particularly in Central, Eastern, and Southeastern Europe. Spatial analyses highlight both positive and negative spillovers: knowledge transfer from productive and educated neighbors fosters growth, while competition from wealthier regions can limit investment and talent attraction.

Keywords: Regional Growth, Bayesian Model Averaging, Spatial Econometrics, Human Capital, European Union, Candidate Countries, Convergence, Spatial Spillovers

Contents

Chapter 1

Introduction and Background

1.1 Opening Remarks

The 2004 "Big Bang" enlargement, which brought ten countries[1] into the European Union (EU), marked a significant milestone in European integration. Since then, the EU has faced numerous challenges, including Brexit, the COVID-19 pandemic, the Russian invasion of Ukraine, and rising inflation. These events have emphasized the importance of EU unity and accelerated accession efforts for Western Balkan countries, Moldova, and Ukraine. However, these regions still face hurdles such as compliance with the *acquis communautaire*, unresolved military conflicts, and persistent corruption Barber (2024).

Regardless of their accession outcomes, the economic future of these Candidate regions remains closely tied to the EU. Identifying the factors driving their economic growth is crucial for shaping policies that promote regional stability and convergence, especially given the dynamic changes in the region. This Thesis investigates convergence trends and key growth drivers in both EU and Candidate regions, using Bayesian Model Averaging (BMA) and spatial economics to provide a comprehensive analysis.

This study finds evidence of convergence among Candidate regions but significant disparities persist between EU member and non-member countries. Key results highlight that human capital—higher levels of tertiary education—significantly boosts regional growth. Industrial activity positively influences growth, while reliance on the construction sector hinders it. Although poorer regions tend to grow faster, convergence is uneven—particularly in Candidate and CEE countries facing structural challenges. This research also uncovers both positive and negative spatial spillover effects: productive and educated neighboring regions foster growth through knowledge transfer, while competition from wealthier neighbors can impede investment and talent attraction elsewhere. These insights emphasize the need for targeted policies to enhance human capital, promote industrial development, diversify economies, and facilitate knowledge transfer to

[1] Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia.

reduce regional disparities and support sustainable growth across Europe.

The Thesis is structured as follows: Chapter 1 introduces the study and its academic background. Chapter 2 outlines the methodology and dataset employed, focusing on BMA. Chapter 3 presents the empirical results, followed by the robustness assessment in Chapter 4. Finally, Chapter 5 concludes.

1.2 Literature Review

This Thesis aligns with the extensive literature on the determinants of economic growth using BMA. As noted by Brock and Durlauf (2001), growth models often face uncertainties regarding theoretical foundations, particularly concerning which determinants should be included, as well as the heterogeneity of countries with similar growth dynamics. BMA addresses these uncertainties by averaging across multiple models rather than selecting a single best model. This approach captures a wide range of potential growth determinants across regions and countries, providing more robust conclusions in light of the open-ended nature of growth theories, where the significance of one theory does not preclude the relevance of others (Brock et al., 2003).

The methodology of this Thesis directly builds on the work of Cuaresma et al. (2014), who employed BMA combined with spatial parameterization to assess growth determinants across a panel of NUTS (Nomenclature des Unités Territoriales Statistiques) level 2 EU regions. That study found significant asymmetries in income convergence between Eastern and Western Europe, highlighting the faster growth potential of regions with higher human capital—particularly those with a larger share of workers holding higher education qualifications—and of regions hosting the capital city, which serve as hotspots of economic activity, competitiveness, and innovation.

D'Andrea (2022) extends this line of inquiry by using various model prior combinations to identify robust growth determinants in Europe. Her research underscores the importance of initial GDP per capita, the share of manufacturing in GDP, and fertility rates as key drivers of growth, supporting the theory of conditional convergence, where countries with lower initial income tend to grow faster. On a more global scale, Moral-Benito (2012) highlights the importance of lower investment prices, geographic proximity to major cities, and higher levels of political rights as positive sources of growth. Further contributing to the political and institutional discourse, Man (2015) employs BMA to analyze whether competition in economic and political arenas is a robust growth determinant. The study concludes that competition, particularly in financial markets, has a positive impact on growth, emphasizing that more competitive environments foster better economic outcomes. Błażejowski et al. (2019) apply BMA to a global dataset and identify that countries following the "Asian development model," characterized by high savings and investment coupled with low initial GDP per capita, experience the highest growth rates.

The concept of convergence is central to growth theories and is closely examined in this Thesis. Convergence describes the process by which poorer countries or regions grow faster than richer ones, thereby reducing income and output disparities. Monastiriotis (2011) investigates regional growth dynamics in CEE countries following the collapse of communism and their transition to market economies. The study finds that while national-level convergence has occurred, it has been accompanied by regional disparities within countries, leading to polarization. Certain regions, such as metropolitan areas and those bordering the EU, experienced faster growth, while others lagged behind.

Focusing more on Candidate countries, particularly the Western Balkans, Bartlett and Prica (2016) notes that while EU accession has driven reforms in these regions, external shocks like the 2007–2008 financial crisis have slowed convergence. Stanišić et al. (2018) suggests that the Western Balkans are not closing the income gap with the EU15 and continue to face significant economic challenges. Factors such as political instability, slower reforms, and vulnerability to external shocks have hindered their economic progress.

Moreover, the literature connects growth theories to policy implications. In their critical assessment, Boldrin and Canova (2001) argue that EU regional policies aimed at reducing income disparities have had limited success in fostering income convergence across EU regions. They highlight that these policies often fail to adequately account for regional heterogeneity and local characteristics, leading to mixed results in terms of reducing economic inequalities. Moreover, they point out that centralized policy decisions do not always align with the specific needs of different regions, potentially limiting the effectiveness of regional development initiatives. Ferry and McMaster (2013) highlight that the impact of EU cohesion policy on domestic regional policies is not uniform. While cohesion policy has significantly fostered Europeanisation and influenced regional policy objectives—such as promoting strategic planning and competitiveness—domestic policy frameworks have often adapted EU approaches to local contexts, leading to accommodation rather than full transformation. They emphasize that the influence of cohesion policy is conditioned by pre-existing regional frameworks, resulting in a varied impact depending on the specific domestic setting.

1.3 Paper Contribution

This project aims to enhance our understanding of regional economic growth by building on the work of Cuaresma et al. (2014). It seeks to replicate their "incremental" methodological framework, applying it to the period from 2009 to 2019 while expanding the analysis to include current EU Candidate countries. This approach updates Cuaresma et al. (2014)'s conclusions within a new temporal and spatial context.

The key innovation of this research is the application of BMA to analyze growth at the NUTS-2 level across both EU Member States and Candidate countries. By employing BMA in this context, the study introduces a novel approach to examining Europe-wide success factors and cross-border disparities, which has the potential to inform policies aimed at enhancing economic cohesion within the EU, while better accounting for parameter heterogeneity in the econometric model.

The research has two primary objectives. First, it seeks to identify the key drivers of regional economic growth across continental Europe, with a particular focus on how various factors contribute to economic performance at the NUTS-2 level. This includes assessing the relative importance of different growth determinants in varying regional contexts. Second, the study aims to uncover asymmetries between clusters of regions, defined by geographic proximity, economic conditions, or socio-political contexts. This analysis will focus on identifying and explaining disparities among EU Member states, recent CEE member states, and Candidate countries, with particular emphasis on the CESEE (Central, Eastern, and Southeastern European) region. By focusing on the interactions between EU Member states and Candidate countries, this research addresses a crucial gap in the literature, providing new insights into economic disparities within CESEE and between these regions and Western Europe.

In light of the renewed focus on EU Enlargement, this study is particularly timely, offering valuable policy implications for promoting economic stability and convergence through instruments such as the EU Cohesion Policy and the Instrument for Pre-Accession Assistance (IPA). Additionally, the shifting economic landscape—marked by EU integration, the COVID-19 pandemic, and geopolitical tensions—has altered the traditional drivers of growth in these regions, making this research especially pertinent to ongoing policy discussions (Gereben and Wruuck, 2021).

Chapter 2

Methodology

2.1 Econometric Model

This study applies BMA to address the issue of model uncertainty, which is common in growth studies due to the large number of potential explanatory variables and model specifications (Brock and Durlauf, 2001). Unlike traditional econometric methods that rely on selecting a single "best" model, BMA averages over a range of models weighted by their posterior probabilities, resulting in more robust and reliable estimates (Hinne et al., 2020).

Following the approach of Cuaresma et al. (2014), we implement three BMA model specifications in a stepwise method. First, a pooled cross-sectional model is estimated for all regions over the period under study. Second, the model is extended to include region-specific fixed effects to control for unobserved heterogeneity. Lastly, a Spatial Autoregressive (SAR) structure is incorporated, adding a spatial lag term to capture spillover effects between neighboring regions. This progression allows for a comprehensive analysis of regional growth by accounting for both cross-regional differences and the spatial correlation inherent in economic growth processes.

Building on Cuaresma et al. (2014), these models can be expressed within the general SAR framework:

$$y = \alpha\iota_N + X_k\vec{\beta}_k + \rho W y + \epsilon, \tag{2.1}$$

where y is the $N \times 1$ vector of the growth rates of income per capita for N regions, α is the intercept term, ι_N is an $N \times 1$ vector of ones, X_k is the $N \times K$ matrix of explanatory variables, β_k represents the corresponding coefficients, W is the $N \times N$ spatial weight matrix capturing spatial dependence, ρ is the spatial autoregressive parameter, and ϵ is the error term. In specifications including fixed effects, region-specific effects are included in the deterministic part of the model, not in the error term. The residuals ϵ are assumed to be independently and identically distributed with zero mean and variance σ^2, such that the covariance matrix is $\Sigma = \sigma^2\mathbf{I}_N$ (Cuaresma et al., 2014).

BMA tackles model uncertainty by estimating all possible combinations of explanatory variables in X_k, constructing a weighted average of these models. With K potential variables, this results in 2^K model combinations, indexed by M_j for $j = 1, \ldots, 2^K$ (Hinne et al., 2020). We can write the posterior distribution of the coefficient β_k as:

$$p(\beta_k|\mathcal{D}) = \sum_{j=1}^{2^K} p(\beta_k|M_j, \mathcal{D})p(M_j|\mathcal{D}),$$

where $\mathcal{D}$ represents the data.

The posterior distribution of β_k, given the data $\mathcal{D}$, is the average of its posterior distributions under each model, weighted by the posterior model probabilities. The posterior model probabilities (PMPs) are derived using Bayes' theorem:

$$p(M_j|\mathcal{D}) = \frac{p(\mathcal{D}|M_j)p(M_j)}{p(\mathcal{D})} = \frac{p(\mathcal{D}|M_j)p(M_j)}{\sum_{j=1}^{2^K} p(\mathcal{D}|M_j)p(M_j)},$$

where $p(\mathcal{D})$ is the integrated likelihood, serving as a constant scaling factor across models and ensuring that the posterior probabilities sum to one. The PMP $p(M_j|\mathcal{D})$ is proportional to the marginal likelihood of model M_j, $p(\mathcal{D}|M_j)$, multiplied by the prior model probability $p(M_j)$.

In this study, a Bayesian linear regression model with Zellner's g-prior is used to reflect prior beliefs about the parameters before observing the data. The prior distribution for the regression coefficients β_k in Equation (2.1), conditional on model M_j, is specified as:

$$p(\beta_k|\sigma^2, M_j) \sim \mathcal{N}\left(0, \sigma^2 g(X_k' X_k)^{-1}\right),$$

where X_k is the matrix of explanatory variables included in model M_j, and g is a key hyperparameter controlling the prior variance of the coefficients. This hyperparameter reflects the degree of confidence in prior beliefs about the coefficients' uncertainty. As discussed by Fernandez et al. (2001), the benchmark value for g is set to $\max(N, K^2)$, where N is the number of observations and K is the total number of covariates. This specification balances the trade-off between overfitting (when g is too small) and underfitting (when g is too large), effectively shrinking the estimates toward zero when information from the data is limited. Zellner's g-prior is widely used because it maintains a structured relationship between the data and the priors. As highlighted by Feldkircher and Zeugner (2015), the g-prior framework results in a marginal likelihood that penalizes larger models, thus preventing overfitting while allowing smaller models to retain a higher likelihood.

The prior on the model space $p(M_j)$ also plays a crucial role in BMA, reflecting beliefs about the likelihood of different models being true before observing the data. A random theta prior inclusion probability for each regressor is used, following Ley and Steel (2009), who suggest a beta-binomial prior distribution, where a beta distribution is employed as a hyper-prior on the inclusion probability. This beta-binomial specification allows for more flexibility by allowing the prior to adapt to the expected model size, making it a better choice when prior information on the model size is limited. The beta-binomial prior mitigates the risk of overfitting by spreading the prior probability across a wider range of possible model sizes, reducing the risk of concentrating too much prior mass on models of a specific size (Feldkircher and Zeugner, 2015). In this application, the expected model size is fixed at $K/2$.

Given the large number of models under consideration (2^K), implementing BMA can be computationally challenging. To efficiently explore this vast model space, BMA employs the Markov Chain Monte Carlo Model Composition (MC^3) method. Rather than evaluating every possible model, the MC^3 algorithm samples from the most relevant part of the posterior distribution, focusing on models with higher posterior probabilities. This allows the algorithm to approximate the posterior model distribution without needing to exhaustively examine all 2^K models.

The MC^3 sampler moves through the space of possible models, and at each step, a candidate model M_j is proposed to replace the current model M_i. The transition probability from model M_i to model M_j is given by:

$$p_{i,j} = \min\left(1, \frac{p(M_j|\mathcal{D})}{p(M_i|\mathcal{D})}\right),$$

where $p(M_j|\mathcal{D})$ and $p(M_i|\mathcal{D})$ are the posterior probabilities of the candidate and current models, respectively. If the candidate model is accepted, it becomes the new current model; otherwise, the sampler remains at M_i and continues to propose new candidate models. Over time, the number of times each model is visited will converge to the true posterior distribution. In this research, the MC^3 sampler was calibrated with 10 million draws and a burn-in period of 3 million iterations. To further enhance the efficiency of this extensive process, a birth-death sampler is used. In this approach, candidate models are generated by either adding a covariate that is not in the current model (a "birth") or dropping a covariate that is present in the current model (a "death"). This method ensures systematic exploration of the model space, allowing the sampler to focus on the most promising regions (Hoeting et al., 1999).

Furthermore, the MC^3 sampler was adjusted to enforce the strong heredity principle, developed by Chipman (1996). According to the strong heredity principle, an interaction between two variables can only be included if both main effects are also present in the model. This helps ensure that the interaction terms are meaningful and interpretable, as their inclusion requires the variables themselves to have an effect. This restriction helps to reduce the complexity of the model space by avoiding spurious interactions that could arise when the main effects are not accounted for.

From the BMA analysis, we obtain the following results: the Posterior Inclusion Probability (PIP), the Posterior Mean (PM), and the Posterior Standard Deviation (and thus the Variance) for each variable. The PIP of each variable x_k is the sum of the probabilities of all models that include x_k:

$$p(\beta_k \neq 0|\mathcal{D}) = \sum_{j:\beta_k \in M_j} p(M_j|\mathcal{D}).$$

It represents the probability that a given variable is included in the "true" model, considering all possible models. Variables with PIP values greater than 0.5 are considered significant. Based on Kass and Raftery (1995), PIP values can be classified as weak (50–75%), substantial (75–95%), strong (95–99%), and decisive (99% or higher).

The posterior mean of β_k is the model-weighted mean of the model-specific posterior means:

$$E(\beta_k|\mathcal{D}) = \sum_{j=1}^{2^K} p(M_j|\mathcal{D}) E(\beta_k|\mathcal{D}, M_j).$$

It is the average effect of a given variable on the dependent variable, calculated across all possible models, weighted by their posterior probabilities.

Finally, the posterior variance accounts for both within-model variance and variance across models:

$$\mathrm{Var}(\beta_k|\mathcal{D}) = \sum_{j=1}^{2^K} p(M_j|\mathcal{D}) \left[\mathrm{var}(\beta_k|\mathcal{D}, M_j) + (E(\beta_k|\mathcal{D}, M_j) - E(\beta_k|\mathcal{D}))^2\right].$$

This expression combines the variance of β_k within each model and the variance of the estimates across different models, providing a comprehensive measure of uncertainty.

2.2 Spatial Weight Matrix $\boldsymbol{W}$

In the SAR model, the spatial weight matrix W plays a critical role in capturing spatial relationships between regions. This matrix defines the structure of spatial dependence by quantifying how each region is influenced by its neighbors. Spatial dependence arises when the value of a variable in one region is affected by the values of that same variable in neighboring regions (LeSage and Parent, 2007). One way to account for this spatial dependence is through the inclusion of spatial components, in form of eigenvectors, which are extracted from the spatial weight matrix W. These eigenvectors capture the underlying spatial patterns within the data, summarizing the spatial relationships in a way that can be incorporated into the regression model. By including these eigenvectors as additional regressors, we effectively address the issue of spatial autocorrelation. This helps reduce multicollinearity that might otherwise distort the regression estimates and improves the robustness of the model (Feldkircher, 2010). Given the panel structure of the data used in this study, the filtering process was applied to the growth rate of GDP per capita over the period from 2009 to 2019. The resulting spatial eigenvectors were then replicated for each observation in the dataset across all 11 years, once for each year. This approach assumes that the average spatial effects, as captured by the eigenvectors, remain constant over the years, reflecting the belief that the spatial relationships between regions do not vary significantly over the time period under study.

To account for the uncertainty and complexity of spatial relationships, multiple spatial weight matrices are considered in the analysis. This approach ensures that the model does not depend on a single, potentially incorrect assumption about spatial interactions, enhancing the reliability of the estimates through BMA. The spatial weight matrices included in the analysis are the inverse distance matrices, first-order and second-order queen-contiguity matrices, and k-nearest neighbors (k-NN) matrices. The inverse distance matrix is defined as:

$$W_{ij} = d_{ij}^{-\phi},$$

where d_{ij} is the distance between regions i and j, and ϕ controls the decay of spatial influence. Both $\phi = 1$ and $\phi = 2$ are used to model varying strengths of spatial interaction. The first-order queen-contiguity matrix assigns equal weights to regions that share a boundary, while the second-order queen-contiguity matrix extends this relationship to include neighbors of neighbors, thereby capturing more distant spatial dependencies[2]. The k-NN matrix defines spatial relationships by selecting the closest k neighbors for each region, with the analysis using a maximum of 5 neighbors.

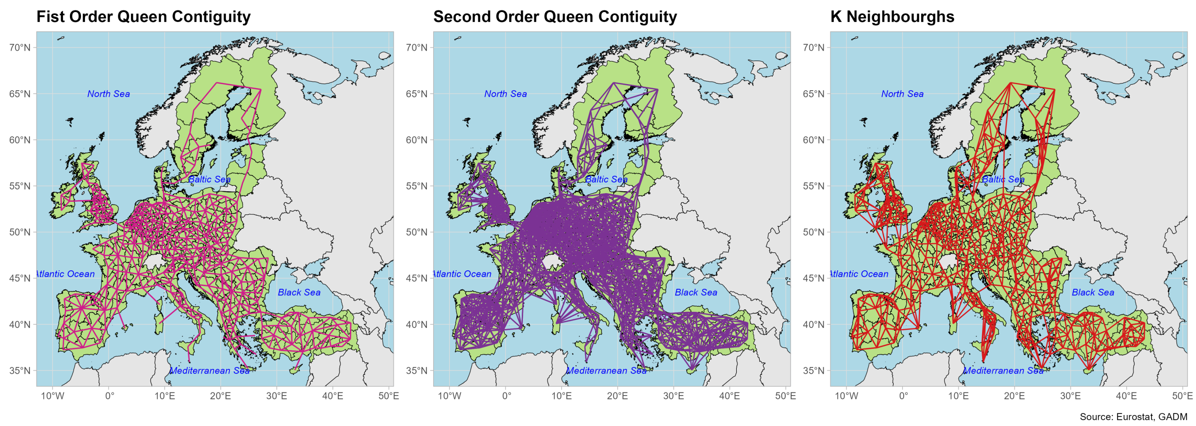


Figure 2.1: Comparison of Spatial Networks

Despite their similarities, these matrices summarize networks in different ways. The inverse distance matrices emphasize weights based on inverse distances, while the conti-

[2]To expand the network, isolated regions without neighbors were connected to the nearest national region or the closest neighboring country. Additionally, infrastructure links, such as the Øresund Bridge between Copenhagen and Malmö and the Eurotunnel between the UK and France, were also accounted for in the network's design.

guity and k-NN matrices focus on binary relationships, indicating whether two regions are neighbors or not. Figure 2.1 visualizes the basic structures of the five spatial matrices used, highlighting the relative density of each matrix.

This comprehensive approach to specifying spatial weight matrices allows for a better understanding of the spatial structure within the data, as BMA integrates over these multiple spatial structures, leading to more reliable and robust estimates while accounting for spatial dependencies and uncertainties.

2.3 Dataset

This study uses a comprehensive pooled dataset of cross-sections to analyze regional economic growth at the NUTS-2 level, covering 301 regions across Europe from 2009 to 2019 (hence, 3311 observations). This period was chosen to avoid distortions from the global financial crisis and the COVID-19 pandemic, ensuring a focus on a relatively stable economic environment. The dataset includes 265 regions from EU Member States and 36 regions from seven official Candidate countries and Kosovo: Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, Serbia, Turkey, and Moldova. Ukraine and Georgia, which received Candidate status in 2022 and 2023 respectively, were excluded due to the scarcity of regional data.

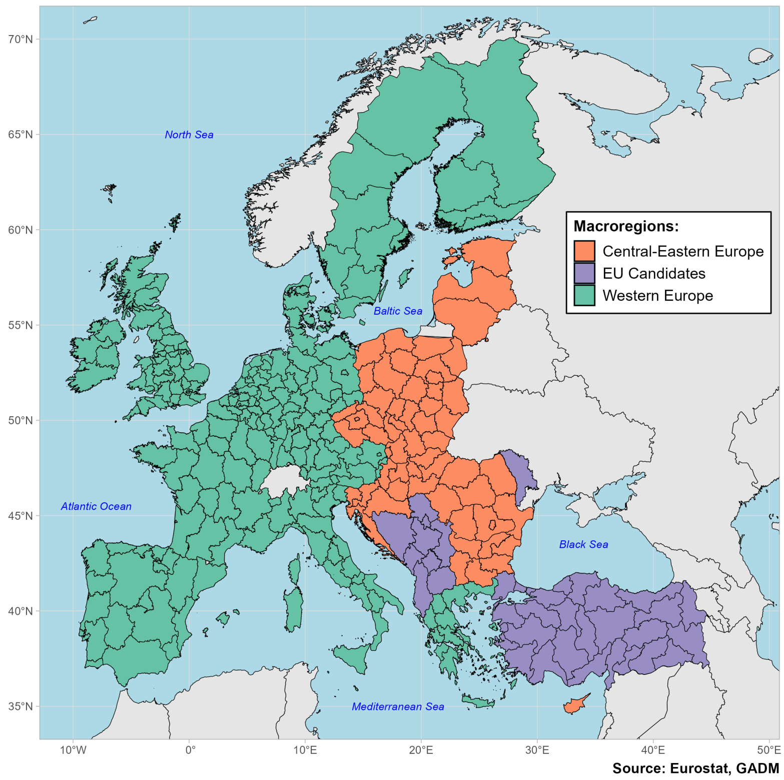


Figure 2.2: NUTS-2 Regions under study

To maintain data consistency, adjustments were made to the territorial units analyzed.

These adjustments aimed to ensure comprehensive data coverage across the European area while preserving regional consistency over time. For example, Albania was treated as a single region despite its official division into three NUTS-2 regions, and some countries, such as Croatia and Lithuania, reverted to previous NUTS-2 classifications when more recent time series data were insufficient. Table A.1 in the Appendix lists all regions, indicating those that differ from the NUTS-2 2021 Classification.

The primary dependent variable is the average annual growth rate of income per capita, adjusted to 2009 prices. The dataset includes 30 explanatory variables organized into thematic groups:

- **Factor accumulation and convergence**: Traditional growth drivers such as income levels, capital investment, and population growth.
- **Demography**: Population density, migration rate, life expectancy, and fertility rate.
- **Human capital**: Educational attainment levels, categorized into tertiary, secondary, and primary education.
- **Sectoral structure and employment**: Sectoral contributions to value added, employment rates, productivity, and NEET rate.
- **Socio-geographical**: Coastal access, island or border specification, status as a capital city or Objective 1 region[3], and Eurozone membership.
- **Interaction terms**: The CEE and Candidate dummies were combined with GDP per capita, sectoral components of GVA, and share of population with tertiary education. Additionally, CEE dummies were interacted with the capital city specification, but not Candidate dummies, since the majority of these countries were treated as single regions.

Primary data sources include Eurostat, ARDECO, and for Candidate countries, the World Bank, Wiener Institut für Internationale Wirtschaftsvergleiche (WiiW), and national statistical offices. Supplementary data were incorporated where necessary, especially from the ESPON database for EU countries. Table A.2 in the Appendix lists all variables, definitions, descriptive statistics, and sources.

All explanatory variables capture the initial values of regions at the start of the sample period, allowing them to be treated as predetermined in the least squares estimation and helping to mitigate potential endogeneity concerns. This is particularly important since the dependent variable reflects annual growth between consecutive years.

[3] Areas where GDP per capita is below 75% of the EU average, making them eligible for financial support to boost economic growth and reduce regional disparities from the EU Cohesion Policy.

Chapter 3

Results

The empirical findings are presented for the three different model specifications discussed in the Methodology Section 2.1. Each model analysis was conducted in three stages, with different sets of regressors. First, only the "core" basic variables were included. In the second stage, the CEE and Candidate dummy variables were introduced. Finally, in the third stage, interaction terms were added. This incremental approach allows for a systematic assessment of the robustness of the results, enabling a comparison of how the significance and magnitude of the estimates change as the model becomes more specific.

The tables report the posterior inclusion probabilities (PIP) of each regressor, together with the posterior mean (PM) and posterior standard deviation (PSD) of the posterior distribution for the associated parameter. The results are obtained from 10 million draws of the MC^3 sampler, after a burn-in phase of 3 million iterations. In all cases, a binomial-beta prior is used, where the expected model size equals $K/2$ regressors. For easier readability, the variables shown in the tables are restricted to those that have PIP ¿ 0.5, which is labeled robust in at least one of the specifications used. Results are obtained with R packages `BMS` and `spat.BMS` developed by Feldkircher and Zeugner (2015). The corresponding code for the whole research is available at my public repository on GitHub.

3.1 Regional Growth Determinants *between* European Regions

The results in Table 3.1 offer valuable insights into the multifaceted drivers of regional growth across EU regions and Candidate countries, using a pooled cross-section of regions.

A prominent finding across all models is the strong negative association between GVA from the construction sector and regional growth. This likely reflects the cyclical and short-term nature of construction-driven investments, which, while stimulating temporary economic activity, do not translate into sustained productivity gains. In regions heavily reliant on the construction sector, this pattern underscores the structural limitations of

Table 3.1: Between Countries - Regional Determinants of Growth

	Model 1			*Model 2*			*Model 3*		
Variable	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**
Unemployment Rate	1.000	-0.118	0.013	0.999	-0.073	0.017	-	-	-
NEET Share	0.999	0.074	0.013	0.813	0.042	0.025	0.717	0.029	0.022
GVA Construction	0.999	-0.150	0.031	0.999	-0.147	0.034	0.998	-0.147	0.032
Investment Rate	0.999	0.052	0.010	-	-	-	-	-	-
GDP per Capita	0.998	-0.017	0.005	-	-	-	-	-	-
GVA Public	0.997	-0.059	0.014	-	-	-	-	-	-
Pop. with Tertiary Edu.	0.986	0.055	0.010	0.983	0.050	0.011	1.000	0.046	0.009
Migration Rate	0.846	-0.273	0.143	0.991	-0.385	0.096	-	-	-
Labor Productivity	0.535	0.005	0.005	0.520	0.006	0.007	0.999	0.018	0.004
GVA Industry	-	-	-	0.690	0.273	0.207	1.000	0.025	0.012
Capital City	-	-	-	0.795	-0.006	0.004	1.000	-0.002	0.003
Wage EUR	-	-	-	-	-	-	0.996	-0.020	0.005
Distance from Buxelles	-	-	-	-	-	-	0.980	-0.000	0.000
CEE/Candidates - Dummy interactions									
Candidates				1.000	0.039	0.004	1.000	0.107	0.011
CEE				1.000	0.023	0.003	1.000	-0.009	0.010
Candidates × GVA Industry							1.000	-0.153	0.020
CEE × Pop. Tertiary Edu							1.000	0.142	0.023
Candidates × Pop. with Tertiary Edu.							1.000	-0.194	0.031
Candidates × Capital City							0.983	-0.025	0.007
CEE × Capital City							0.999	-0.026	0.005
Share of posterior probabilities - Best model		0.25			0.14			0.11	
Share of posterior probabilities - Top 25 models		0.80			0.71			0.45	
Share of posterior probabilities - Top 50 models		0.87			0.78			0.53	
Corr PMP		1.0000			1.0000			0.9999	
Adjusted R^2		0.37			0.39			0.42	

Notes: PIP, posterior inclusion probability; PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov chain Monte Carlo model composition (MC3) sampling with 3 million burn-ins and 10 million posterior draws. Time fixed effects were included across all model specifications. Model 1: Cross-section of regions (baseline). Model 2: Cross-section of regions including the Central and Eastern Europe (CEE) and Candidates dummy variable. Model 3: Cross-section of regions further including interaction terms. Under Model 3 the 'strong heredity prior' was employed.

depending on non-tradable sectors, which often lack the productivity-enhancing effects seen in more innovation-driven, tradable industries. This result might also be traced back to the contraction of the overall sector, as observed in sectoral reports focusing on Europe (Baker et al., 2017) and globally (Mischke et al., 2024). In fact, there are concerns about the low productivity of the sector, which since the 2009 recession has struggled to fully recover, with increasing costs harming its profitability.

In contrast, GVA from industry exerts a consistently positive effect on growth. Industry tends to represent a broader mix of high-productivity sectors, including manufacturing and advanced technology industries, which are integral to driving competitiveness and long-term economic expansion. This result highlights the critical importance of fostering a balanced sectoral composition in regional economies, particularly for those seeking to enhance their industrial base.

Human capital, measured by the population share with tertiary education, emerges as a robust positive determinant of regional growth across all models. This finding corroborates the conclusions of Cuaresma et al. (2014) and other studies highlighting the importance of education as a driver of economic performance, especially in the context of knowledge-based economies. Highly educated populations provide regions with enhanced capacity for innovation and adaptation to technological changes, both of which are critical for sustaining growth.

Similarly, labor productivity demonstrates a strong positive relationship with growth, highlighting the critical role of productivity-enhancing sectors in driving regional economic performance. Regions with higher labor productivity are generally more competitive, attracting investment and fostering long-term economic resilience. This finding underscores the importance of prioritizing productivity-enhancing policies, such as improving labor skills and investing in advanced technologies, which can position regions for sustained growth.

The results on GDP per capita and gross wages provide evidence in favor of the convergence hypothesis. Poorer regions, indicated by lower GDP per capita, tend to grow faster as they catch up with wealthier regions. However, the lack of significance in some models suggests that wages might be capturing the convergence effect more strongly. In regions with high wages, economic growth slows, reflecting the diminishing returns associated with higher levels of development. This alternating significance might result from the high collinearity of the two variables.

The convergence effect is also evident in the interaction terms with CEE regions and Candidate countries. The initial higher growth rates in these regions support the notion that poorer regions can grow more rapidly, benefiting from knowledge and capital transfers from wealthier areas. However, the nuanced role of human capital in CEE regions indicates that only regions with high levels of education have been able to capitalize on this growth potential, reinforcing the importance of skills and education in achieving sustained regional growth, and highlighting the need to account for parameter heterogeneity to accurately uncover these trends.

The significant differences between CEE regions, Candidate countries, and more developed EU regions provide insights into the challenges and opportunities for regional policy. The high significance of the CEE and Candidate dummy variables suggests that these regions continue to exhibit higher growth potential due to their lower initial income levels. However, deeper structural reforms are necessary, particularly in Candidate countries, to enhance productivity and industrial capacity.

In fact, the negative interaction between Candidate countries and GVA from industry suggests that these regions face specific challenges in transitioning to more industrialized economies. Despite recent improvements in the sophistication of Western Balkans business processes, as observed in Shimbov et al. (2019), structural reforms that can enhance the productivity of industrial sectors and foster innovation are still needed across all Candidate countries to realize the full growth potential of these regions.

The results should be interpreted with caution, especially when assigning direct causal relationships. The NEET share provides a clear example of this. The positive coefficient associated with this variable should not be understood as an indication that higher percentages of youth who are neither employed nor in education have a favorable impact on economic growth. Rather, it suggests that regions experiencing the most growth tend to exhibit this characteristic, possibly due to other underlying factors. This reflects the higher NEET share observed in Candidate countries (an average of 27.9% in 2019), compared to EU members, where the average was 13.5% in CEE countries and 11.7% in Western Europe. Alternatively, the unexpected sign of the coefficient could also be linked to multicollinearity with the Unemployment Rate, which, as expected, shows a negative coefficient, consistent with classical growth theories.

The relatively high degree of model uncertainty, as evidenced by the share of posterior probabilities across the top models, justifies the use of BMA. Rather than relying on a single "best" model, BMA allows us to incorporate the weighted contributions of many models, thus providing a more robust and comprehensive picture of the determinants of regional growth. The stable and high correlation between posterior model probabilities further enhances confidence in these findings. In Appendix A.3, the single best model results alongside some regression diagnostics are reported; however, they do not differ considerably from the overall BMA performance.

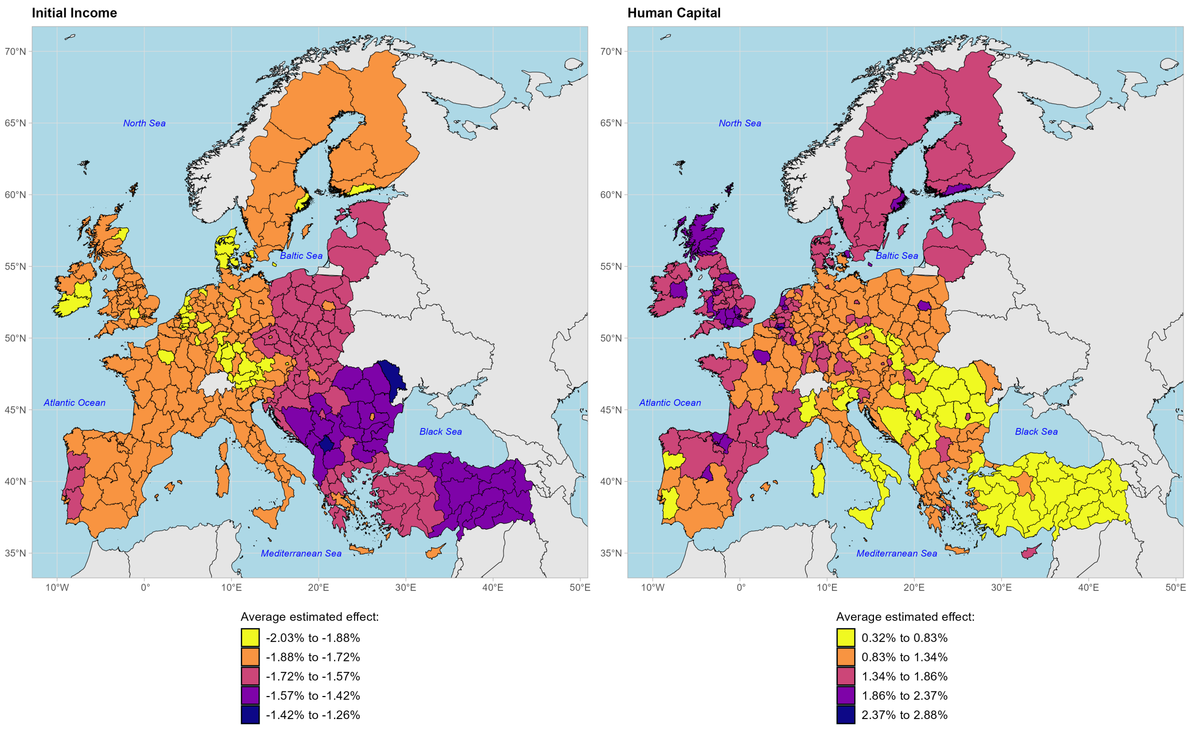


Figure 3.1: Distribution of Effects

Displaying the spatial distribution of the effects of initial income and human capital on growth reveals how these variables differently impact regional economic performance. This provides crucial insights into the dynamics of convergence and the role of human capital in fostering regional development.

In the left-side map of Figure 3.1, regions located primarily in Candidate countries, CEE, Portugal and Turkey are expected to grow more rapidly relative to wealthier regions due to their lower economic base. These areas, shaded in darker tones, reflect a stronger negative impact of initial income on growth, consistent with the theory of conditional convergence. This suggests that poorer regions have more room for rapid expansion as they "catch up" to more developed areas. Conversely, the lighter-colored regions—those within the so-called European backbone[4] (Brunet et al., 1989), stretching from the UK and Ireland across Germany and France to Northern Italy and Scandinavia—experience a much smaller negative effect, or even a modestly positive one. These wealthier regions, having already captured much of their potential for rapid economic gains, now face slower growth rates, in line with the theory that higher initial income levels tend to yield diminishing returns on growth. However, the variation in the intensity of this effect, particularly in the darkest-shaded regions, suggests that not all poorer areas are equally well positioned for rapid growth. The challenge for these regions lies not just in their lower starting income but in overcoming structural barriers such as inadequate infrastructure, insufficient human capital, and institutional weaknesses. Without addressing these factors, the expected convergence might not materialize as rapidly or as uniformly as theory would suggest.

The right-side map, depicting the effect of human capital on growth, tells a different story. Human capital is widely recognized as a key driver of long-term economic performance, especially in knowledge-based economies. Regions with high levels of education and skills—particularly parts of the UK, the Nordic countries, and capital regions—are shown to benefit from a strong positive relationship between human capital and growth. The darker shades in these regions indicate that they are reaping significant economic benefits from their investments in education and skills development. This is especially evident in areas where high levels of productivity, innovation, and advanced industries drive economic activity. In contrast, many regions within the Candidate countries, rural CEE, and Southern Italy do not experience the same robust growth linked to educational attainment. This disparity highlights a crucial policy implication: for these regions to accelerate their growth, substantial investments in education and workforce training are essential. Without such improvements, they risk being left behind, especially as global competition increasingly relies on knowledge, skills, and innovation. In the absence of targeted educational reforms and investment in human capital, these regions may struggle to fully unlock their growth potential, thus perpetuating existing economic disparities within the broader European context.

[4] Also known as the Blue Banana zone, it encompasses European regions with historically higher wage levels and industrial activity.

3.2 Regional Growth Determinants *within* European Countries

Table 3.2 displays the results for the baseline model expanded with country fixed effects. The inclusion of country fixed effects in a regression model helps control for unobserved heterogeneity between countries, capturing any country-specific characteristics that may influence regional growth but remain constant over time. By accounting for these fixed effects, the model isolates within-country variation, allowing us to observe how the determinants of growth affect regions differently within the same country.

Table 3.2: Within Countries - Regional Determinants of Growth

	Model 1			*Model 2*		
Variable	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**
GVA Construction	0.999	-0.284	0.042	0.999	-0.295	0.036
NEET Share	0.996	0.102	0.022	-	-	-
Pop. with Primary Edu.	0.900	-0.066	0.026	0.977	-0.067	0.015
Unemployment Rate	0.867	-0.069	0.033	-	-	-
GDP per Capita	0.793	-0.010	0.006	0.996	-0.025	0.007
GVA Public	-	-	-	0.650	-0.042	0.035
CEE/Candidates - Dummy interactions						
Candidates×GVA Services				0.995	0.135	0.026
CEE×GDP per Capita				0.998	0.049	0.014
Candidates×GDP per Capita				0.993	-0.041	0.008
CEE×Capital City				0.846	-0.022	0.011
CEE×GVA Public				0.665	0.142	0.111
Share of posterior probabilities - Best model		0.12			0.09	
Share of posterior probabilities - Top 25 models		0.72			0.66	
Share of posterior probabilities - Top 50 models		0.80			0.72	
Corr PMP		0.9998			1.0000	
Adjusted R^2		0.46			0.48	

Notes: PIP, posterior inclusion probability; PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov chain Monte Carlo model composition (MC3) sampling with 3 million burn-ins and 10 million posterior draws. Model 1: Cross-section of regions with country-fixed effects. Model 2: Cross-section of regions further including the interaction terms. Time and country fixed effects were included as fixed regressors in both models. The CEE and Candidates dummy variables were left out because of perfect multicollinearity, thus the 'strong heredity prior' was not implemented.

Consistent with previous findings, we observe that the sectoral composition of GVA continues to play a significant role in determining regional growth, with the construction and public sectors identified as hindering factors. The negative impact of the construction sector can be attributed to its cyclical nature and its lack of exposure to competition and innovation as a non-tradable sector. Similarly, the public sector, while essential for delivering public services, often creates inefficiencies when it dominates the local economy. Public sector employment and spending can crowd out private investment, limiting opportunities for private sector dynamism. Without the competitive pressures inherent in private industry, the public sector typically does not drive the innovation or productivity improvements crucial for long-term economic growth. This is particularly concerning for regions heavily dependent on public sector GVA, as they may struggle to develop the dynamic, high-productivity industries needed to sustain growth.

However, the situation differs in CEE regions, where the public sector continues to play a vital role. In these areas, local government spending remains a key engine for growth, especially in transitioning economies that require substantial public investment to address infrastructure and institutional gaps. This result aligns with the research of Zugravu and Ştefania Sava (2014), which shows a positive relationship between public expenditures and economic growth, although sometimes constrained by the level of infrastructure development and economic maturity.

Turning to the role of initial income, we observe a nuanced effect across different regions. In Candidate countries, evidence of convergence is apparent—regions with lower initial income levels grow faster, thereby catching up to wealthier counterparts. Conversely, in CEE countries, the results of the corresponding interaction term indicate growing inequality and regional disparities, with wealthier regions continuing to outpace poorer ones. This trend of divergence within CEE countries has been documented in other studies and highlights the challenges faced by lagging rural regions in accessing capital, innovation, and skilled labor. These regions may lack the institutional strength and resources needed to fully integrate into the broader European growth trajectory, leading to further polarization between core and peripheral areas.

Regarding capital city regions, the results reveal contrasting trends compared to findings in other literature, such as Cuaresma et al. (2014) or Egri and Lengyel (2024), which span periods before and after the one considered in this thesis. In both the previous model specification (Table 3.1) and the within-country analysis, regions hosting capital cities appear to have grown less than expected. The direct explanation for this result is not immediately clear. One possible interpretation is that the model may be capturing broader trends where other metropolitan centers have experienced more significant growth. Alternative explanations might include saturation effects in capital city regions, with limited room for further expansion compared to emerging urban centers. Additionally, infrastructure and housing constraints, higher costs of living, or policy shifts favoring decentralization could have dampened growth in these areas. Further analysis, particularly focusing on regional dynamics and policy interventions, is required to fully understand these results.

A key determinant of regional growth within countries is the level of education. The results show that a higher proportion of the population with only primary education hinders growth, as these regions lack the skilled labor necessary to drive innovation and productivity improvements. This reinforces the critical role of human capital in fostering economic development.

3.3 Spatial Modelling of Growth Determinants in Europe

The final model specification in Table 3.3 expands upon the baseline by removing spatial autocorrelation from the residuals through the inclusion of eigenvectors derived from spatial weight matrices. These eigenvectors capture latent spatial patterns and are incorporated as additional regressors in the BMA framework, allowing for the control of spatial spillovers while estimating the impact of growth determinants (Feldkircher, 2010). This approach provides deeper insights into the drivers of regional growth across Europe, accounting for both spatial dependencies and variable uncertainty.

Table 3.3: Spatially Filtered Regional Growth Determinants

	Model 1			*Model 2*			*Model 3*		
Variable	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**
GVA Construction	0.999	-0.231	0.035	0.999	-0.227	0.034	1.000	-0.205	0.032
NEET Share	0.994	0.081	0.020	0.994	0.082	0.020	0.719	0.029	0.022
Pop. with Tertiary Edu.	0.968	0.044	0.013	0.947	0.043	0.015	1.000	0.058	0.011
Unemployment Rate	0.954	-0.062	0.022	0.960	-0.064	0.022	-	-	-
Labor Productivity	0.950	0.012	0.004	0.911	0.011	0.005	0.960	0.012	0.004
GDP per Capita	0.719	-0.010	0.007	0.661	-0.009	0.008	-	-	-
Gross Wage	0.694	-0.010	0.008	0.698	-0.010	0.007	0.998	-0.021	0.005
GVA Industry	-	-	-	-	-	-	0.996	0.015	0.010
CEE/Candidates - Dummy interactions									
Candidates							1.000	0.064	0.011
Candidates×Pop. with Tertiary Edu.							1.000	-0.203	0.028
Candidates×GVA Industry							0.996	-0.099	0.018
Share of posterior probabilities - Best model		0.07			0.05			0.17	
Share of posterior probabilities - Top 25 models		0.46			0.37			0.65	
Share of posterior probabilities - Top 50 models		0.54			0.45			0.74	
Corr PMP		0.9999			0.9998			0.9948	
Adjusted R^2		0.37			0.39			0.42	

Notes: PIP, posterior inclusion probability; PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov chain Monte Carlo model composition (MC3) sampling with 3 million burn-ins and 10 million posterior draws. Model 1: Cross-section of regions with spatial eigenvectors. Model 2: Cross-section of regions including the Central and Eastern Europe (CEE) and Candidates variable. Model 3: Cross-section of regions further including interaction terms. Under Model 3 the 'strong heredity prior' was employed. Time fixed effects were not included as fixed regressors because of the `spatFilt.bms()` function argument's limitation.

In this final model specification, GVA from both the construction and industry sectors remains key to explaining regional growth, along with human capital, labor productivity, and initial income. Initial income is also represented by wage levels, which again emerge as a driver of convergence, reaffirming the consistent pattern across the models that poorer regions tend to grow faster as they catch up with wealthier ones. The Candidate country dummy is significant, unlike that of the CEE regions, likely due to the pronounced disparities between more developed urban areas and less developed rural regions within these countries. This suggests that while Candidate regions are on a path toward convergence, substantial gaps between regions—even within the EU—are still present. The model also captures the ongoing structural challenges in Candidate countries, where strengthening the education system and fostering industrial growth remain critical to sustaining long-term growth.

Given the importance of the spatial dimension in this model, it is necessary to address the aspect of spatial autocorrelation. However, in this analysis, spatial autocorrelation was not emphasized, primarily because the panel structure of the dataset affects the representation of spatial connections over time. The repetition of spatial interactions across multiple years can dilute or obscure the actual spatial relationships between regions, as temporal dynamics may complicate the spatial structure.

When examining the cross-sectional dataset, which aggregates GDP growth over the entire decade from 2009 to 2019 (301 observations), spatial autocorrelation characteristics similar to those found in Cuaresma et al. (2014) were observed, namely of weak positive correlation. In contrast, the panel dataset with annual GDP growth (3,311 observations) exhibited almost no spatial autocorrelation. Several factors may contribute to this weak spatial autocorrelation. First, Moran's I, commonly used to detect spatial autocorrelation, is primarily designed for purely spatial data, and its effectiveness diminishes when applied to panel data where temporal dependencies interact with spatial relationships. Second, annual GDP growth rates capture short-term fluctuations, and key spatial dependencies may not be reflected in the residuals, especially if significant regional factors are accounted for in the model. Finally, the inclusion of key explanatory variables may explain much of the spatial variation, leaving little residual spatial autocorrelation.

Despite these challenges, incorporating spatial effects in the model has enhanced our understanding of regional growth drivers in Europe, even when spatial autocorrelation is weak or difficult to detect. The results underscore the importance of sectoral composition, human capital, labor productivity, and initial income, while revealing persistent regional disparities, especially in Candidate countries. Policymakers should prioritize education, productivity, and industrial diversification in underperforming regions to achieve more balanced and sustainable growth across Europe.

Chapter 4

Robustness Check

Robustness checks were performed to ensure the reliability and consistency of the results. First, the analysis was repeated using a dataset where missing observations were imputed via the `mice()` function. Unlike the baseline imputation method, `amelia()`, which is tailored for panel data structures, `mice()` works iteratively by imputing each incomplete variable separately, using both observed and previously imputed values of other variables as predictors. Despite these differences in imputation techniques, no notable changes in the significance or magnitude of the results were found when comparing the imputed `mice` dataset to the `amelia` dataset[5].

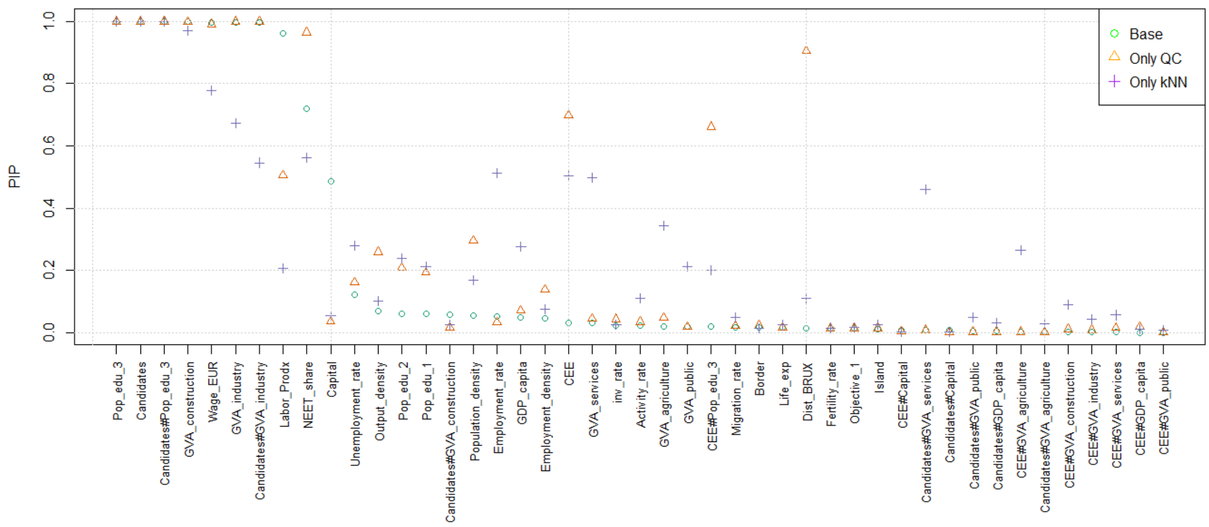
Second, the issue of multicollinearity, which arises from high correlations among several covariates, was addressed. Multicollinearity can lead to inflated standard errors in single-parameter estimates, thereby reducing the precision of the results. To mitigate this, the dilution prior introduced by George (2007) was applied. This prior penalizes models with highly collinear variables by incorporating the determinant of the correlation matrix into the prior model probability. While the determinant approaches 1 for uncorrelated regressors, it tends toward zero for highly correlated variables. After implementing this approach, the results remained qualitatively consistent with those obtained in the primary analysis[6].

Third, various combinations of spatial weight matrices were tested to account for spatial dependencies in the data. Initially, the combination of five spatial matrices was evaluated, where the first inverse distance weight matrix appeared to dominate. To refine the analysis, spatial filtering was performed using subsets of eigenvalues from the first and second-order queen contiguity matrices only, as well as k-NN matrix only, to assess the effects of different network specifications on posterior model probabilities (PMPs).

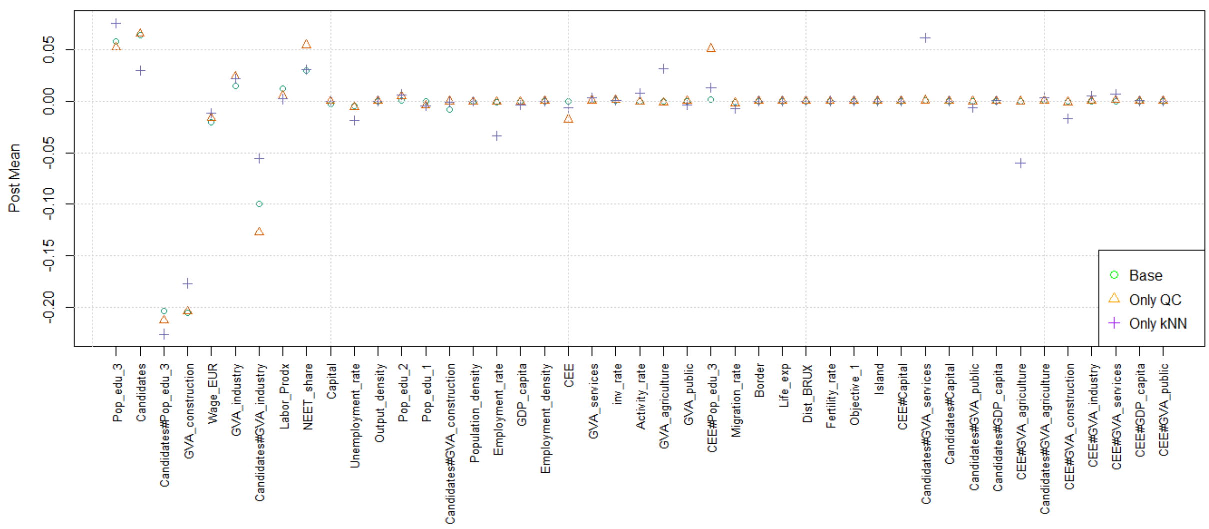
As shown in Figure 4.1a, the significance of certain variables fluctuates considerably across different spatial model combinations. Specifically, while some variables consistently exhibit high posterior inclusion probabilities (PIPs), others show marked variabil-

[5]Result tables are available on demand by contacting the author.

ity depending on the spatial matrix used. This variability underscores the importance of including multiple spatial matrices in the analysis to capture diverse spatial relationships. The "base" specification, which includes all spatial matrices, appears to be the most logical and comprehensive approach, allowing the model to identify the optimal spatial structure that best reflects the spillover effects across regions among the five networks included.



(a) Effects of Spatial Matrices on PIPs



(b) Effects of Spatial Matrices on PMs

Figure 4.1: Effects of Spatial Matrices on BMA Results

In Figure 4.1b, we observe how the posterior means (PMs) vary across three model specifications. The results demonstrate consistency, with the majority of variables showing minimal variation in their PMs across the different models. This consistency indicates that the spatial weighting method does not substantially affect the core relationships in the model, confirming the robustness of the results.

Fourth, to further investigate the transmission channels of growth spillovers, an unrestricted Spatial Durbin Model (SDM) was estimated. This involved expanding the set of potential growth determinants by introducing spatial lags of the explanatory variables. The spatially lagged variables in the models capture the extent to which economic outcomes in neighboring regions influence the growth of a focal region. The presence of such spillover effects is indicative of regional interdependencies within the European Union and its Candidate countries. The results remained largely consistent with those from the benchmark model, reinforcing the robustness of the findings. In some cases, the spatially lagged covariates emerged as significant determinants of regional growth.

Table 4.1: Spatially Lagged Regional Growth Determinants

	Model 1			*Model 2*			*Model 3*		
Variable	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**	**PIP**	**PM**	**PSD**
W GDP per Capita	1.000	-0.0443	0.0092	0.999	-0.0255	0.0056	0.999	-0.0242	0.0052
W GVA Construction	1.000	-0.347	0.0448	1.000	-0.318	0.0438	1.000	-0.367	0.0404
W Labor Productivity	0.999	0.0264	0.0063	0.770	0.0171	0.0110	1.000	0.0382	0.0057
W Unemployment Rate	0.998	-0.112	0.0177	-	-	-	-	-	-
Wage	0.758	-0.0109	0.0067	-	-	-	0.999	-0.0213	0.0067
Pop. with Tertiary Edu.	0.981	0.0431	0.0108	0.975	0.0432	0.0112	0.996	0.0619	0.0086
GVA Industry	-	-	-	-	-	-	0.888	0.0280	0.0130
Output Density	0.520	-0.0001	0.0001	-	-	-	0.690	-0.00004	0.00005
Capital	-	-	-	0.909	-0.0079	0.0032	-	-	-
Migration Rate	-	-	-	0.850	-0.319	0.158	-	-	-
CEE/Candidates - Dummy interactions									
Candidates				1.000	0.0416	0.0038	0.654	0.0349	0.0288
CEE				1.000	0.0258	0.0032	-	-	-
W Candidates×Capital							1.000	-0.0480	0.0082
W CEE×Capital							0.999	-0.0454	0.0071
Candidates×Pop. with Tertiary Edu.							0.999	-0.204	0.0427
W CEE×Pop. with Tertiary Edu.							0.993	0.148	0.0245

Notes: PIP, posterior inclusion probability; PM, posterior mean; PSD, posterior standard deviation. All calculations are based on Markov Chain Monte Carlo Model Composition (MC^3) sampling with 3 million burn-ins and 10 million posterior draws. Model 1: Cross-section of regions with spatially lagged variables. Model 2: Cross-section of regions including CEE and Candidates variables. Model 3: Cross-section of regions with interaction terms. Spatial lags of variables are denoted by W.

The spatial lag of GDP per capita consistently shows a negative impact across all models, as indicated by high PIP values and negative posterior means. This suggests that regions surrounded by wealthier neighbors tend to experience slower growth. One possible interpretation is that wealthier neighboring regions may attract investment, labor, and resources away from the focal region, creating competitive pressures. This finding aligns with the broader literature, where competition effects can lead to reduced growth prospects for regions adjacent to wealthier areas (Maras, 2022). In contrast, the indirect effect of labor productivity is positive, indicating that higher productivity in neighboring regions fosters growth in the focal region. This suggests the presence of positive spillover effects through mechanisms such as knowledge transfer, technology diffusion, and integrated supply chains. This is consistent with Özyurt and Dees (2015), who highlight the importance of spillover effects in boosting regional growth, particularly through the spread of technology and best practices across borders. Productive regions can act as growth engines that drive broader economic development. The spatial lag of GVA from the construction sector shows a negative impact, suggesting that a higher concentration of construction activity in neighboring regions may detract from growth in the focal region. This could be due to competition for investment and labor in the construction sector, or it might reflect the cyclical and localized nature of construction activity.

The interaction terms involving spatial lags provide additional insights. The spatial lag of the interaction of both Candidate and CEE dummies with capital city regions shows a negative coefficient, indicating that neighboring regions to these cities tend to experience slower growth, likely due to the competitive advantages and opportunities concentrated in these metropolitan areas. Similarly, the spatial lag of the interaction between CEE regions and population with tertiary education shows a positive coefficient. This indicates that higher levels of human capital in neighboring CEE regions have a significant positive spillover effect, underlining the role of education and knowledge diffusion in fostering shared growth.

Overall, the inclusion of spatially lagged variables in the model provides evidence of both positive and negative spillover effects across regions. While the models do not deviate substantially from the baseline SAR approach, the SDM version allows for a more nuanced understanding of how regional interdependencies influence growth. The variability in significant coefficients across different model specifications may be due to the complexity of the panel data structure and the challenges in accurately capturing spatial relationships over time. Adjustments made to the spatial weight matrix for use in the panel dataset may have also introduced some instability in the results. Nevertheless, the key findings remain robust, highlighting the importance of considering spatial spillovers in regional growth analysis.

Chapter 5

Conclusion

This study provides a comprehensive analysis of the determinants of regional economic growth across European regions and Candidate countries from 2009 to 2019. Utilizing BMA and spatial econometric techniques, the research has identified key factors influencing growth and highlighted the spatial dependencies inherent in regional development.

The empirical results consistently underscore the critical role of human capital in fostering regional growth. Specifically, the proportion of the population with tertiary education emerges as a robust positive determinant across all model specifications. This finding aligns with the theoretical expectation that educated populations enhance a region's capacity for innovation, adaptability, and competitiveness in a knowledge-based economy.

Sectoral composition also plays a significant role. GVA from the industrial sector positively influences growth, highlighting the importance of high-productivity industries in driving economic expansion. In contrast, reliance on the construction sector negatively impacts growth, reflecting the sector's cyclical nature and limited contribution to long-term productivity gains. These results suggest that regions should strive for a balanced sectoral mix, promoting industries that offer sustainable growth prospects.

The analysis provides evidence supporting the convergence hypothesis, with poorer regions exhibiting faster growth rates as they catch up to wealthier counterparts. However, the convergence process is not uniform across all regions. Candidate countries, in particular, face persistent disparities and structural challenges that hinder their growth potential. The negative interaction effects between Candidate countries and variables such as human capital and industrial GVA indicate that these regions may not fully benefit from the growth drivers that propel other European regions.

Spatial spillovers were examined through the inclusion of spatial eigenvectors and the estimation of a Spatial Durbin Model. The findings reveal both positive and negative spillover effects. While higher productivity in neighboring regions fosters growth through knowledge transfer and innovation diffusion, competition from wealthier neighbors and capital cities can impede a region's ability to attract investment and talent. These spatial dynamics emphasize the importance of considering regional interdependencies in policy formulation.

The results have significant policy implications for the European Union's cohesion policy and Candidate countries aspiring to join the EU. For the EU, the findings highlight the necessity of targeted interventions to reduce regional disparities and promote inclusive growth. Policies should focus on:

- **Investing in Human Capital:** Enhancing education and skills training to build a highly qualified workforce capable of driving innovation and adapting to technological advancements.
- **Promoting Industrial Development:** Supporting the expansion of high productivity industries through incentives, infrastructure development, and access to finance.
- **Diversifying Economic Structures:** Encouraging regions to reduce over-reliance on sectors like construction by fostering a more diversified and resilient economic base.
- **Facilitating Knowledge Transfer:** Strengthening networks between regions to enhance positive spillover effects, leveraging the growth of more developed areas to benefit lagging regions.

For Candidate countries, the challenges are more pronounced due to structural limitations and institutional weaknesses. Policy priorities should include:

- **Educational Reforms:** Substantially investing in education systems to improve access and quality, particularly in higher education, to build human capital.
- **Structural Reforms:** Implementing reforms to improve governance, reduce bureaucratic obstacles, and boost industrial sectors, focusing on innovation and integration into European value chains.
- **Addressing Regional Disparities:** Designing region-specific policies that account for local needs and potentials, ensuring that rural and less-developed areas are not left behind.

Future research could build upon this work by exploring the temporal evolution of spatial dependencies, incorporating more recent data, and examining the impact of specific EU policies on regional growth. Additionally, investigating the role of innovation, digitalization, and environmental sustainability could provide further insights into fostering resilient and inclusive growth across European regions.

Appendix A

Additional Material

A.1 NUTS-2

Nomenclature des Unités Territoriales Statistiques (NUTS)-2 Regions

Albania [S]		
Austria [9]		
Burgenland	Niederösterreich	Wien
Kärnten	Steiermark	Oberösterreich
Salzburg	Tirol	Vorarlberg
Bosnia and Herzegovina [S]		
Belgium [11]		
Région de Bruxelles-Capitale/ Brussels Hoofdstedelijk Gewest	Prov. Antwerpen	Prov. Limburg
Prov. Oost-Vlaanderen	Prov. Vlaams-Brabant	Prov. West-Vlaanderen
Prov. Brabant wallon	Prov. Hainaut	Prov. Liège
Prov. Luxembourg	Prov. Namur	
Bulgaria [6]		
Severozapaden	Severen tsentralen	Severoiztochen
Yugoiztochen	Yugozapaden	Yuzhen tsentralen
Cyprus [S]		
Kypros		
Czech Republic [8]		
Praha	Strední Cechy	Jihozápad
Severozápad	Severovýchod	Jihovýchod
Strední Morava	Moravskoslezsko	
Germany [38]		
Stuttgart	Karlsruhe	Freiburg
Tübingen	Oberbayern	Niederbayern
Oberpfalz	Oberfranken	Mittelfranken
Unterfranken	Schwaben	Berlin
Brandenburg	Bremen	Hamburg
Darmstadt	Gießen	Kassel
Mecklenburg-Vorpommern	Braunschweig	Hannover
Lüneburg	Weser-Ems	Düsseldorf
Köln	Münster	Detmold
Arnsberg	Koblenz	Trier

(Continued)

NUTS-2 Regions. Continued

Rheinhessen-Pfalz	Saarland	Dresden
Chemnitz	Leipzig	Sachsen-Anhalt
Schleswig-Holstein	Thüringen	
Denmark [5]		
Hovedstaden	Sjælland	Syddanmark
Midtjylland	Nordjylland	
Estonia [S]		
Eesti		
Greece [13]		
Attiki	Voreio Aigaio	Notio Aigaio
Kriti	Anatoliki Makedonia, Thraki	Kentriki Makedonia
Dytiki Makedonia	Ipeiros	Thessalia
Ionia Nisia	Dytiki Ellada	Sterea Ellada
Peloponnisos		
Spain [16]		
Galicia	Principado de Asturias	Cantabria
País Vasco	Comunidad Foral de Navarra	La Rioja
Aragón	Comunidad de Madrid	Castilla y León
Castilla-la Mancha	Extremadura	Cataluña
Comunidad Valenciana	Illes Balears	Andalucía
Región de Murcia		
Finland [4]		
Länsi-Suomi	Helsinki-Uusimaa	Etelä-Suomi
Pohjois- ja Itä-Suomi		
France [22]		
Île de France	Centre - Val de Loire	Bourgogne
Franche-Comté	Basse-Normandie	Haute-Normandie
Nord-Pas-de-Calais	Picardie	Alsace
Champagne-Ardenne	Lorraine	Pays-de-la-Loire
Bretagne	Aquitaine	Limousin
Poitou-Charentes	Languedoc-Roussillon	Midi-Pyrénées
Auvergne	Rhône-Alpes	Provence-Alpes-Côte d'Azur
Corse		
Croatia [2]		
Jadranska Hrvatska (NUTS 2016)	Kontinentalna Hrvatska (NUTS 2016)	
Hungary [7]		
Közép-Magyarország (NUTS 2013)	Közép-Dunántúl	Nyugat-Dunántúl
Dél-Dunántúl	Észak-Magyarország	Észak-Alföld
Dél-Alföld		
Ireland [3]		
Northern and Western	Southern	Eastern and Midland
Italy [21]		
Piemonte	Valle d'Aosta/Vallée d'Aoste	Liguria
Lombardia	Abruzzo	Molise
Campania	Puglia	Basilicata
Calabria	Sicilia	Sardegna
Provincia Autonoma di Bolzano/Bozen	Provincia Autonoma di Trento	Veneto
Friuli-Venezia Giulia	Emilia-Romagna	Toscana
Umbria	Marche	Lazio

(Continued)

NUTS-2 Regions. Continued

Lithuania [S]		
Lietuva (NUTS 2013)		
Luxembourg [S]		
Latvia [S]		
Latvija		
Moldova [S]		
Montenegro [S]		
Crna Gora		
North Macedonia [S]		
Severna Makedonija		
Malta [S]		
Netherlands [12]		
Groningen	Friesland	Drenthe
Overijssel	Gelderland	Flevoland
Utrecht	Noord-Holland	Zuid-Holland
Zeeland	Noord-Brabant	Limburg
Poland [17]		
Malopolskie	Slaskie	Wielkopolskie
Zachodniopomorskie	Lubuskie	Dolnoslaskie
Opolskie	Kujawsko-Pomorskie	Warminsko-Mazurskie
Pomorskie	Lódzkie	Swietokrzyskie
Lubelskie	Podkarpackie	Podlaskie
Warszawski stoleczny	Mazowiecki regionalny	
Portugal [5]		
Norte	Algarve	Centro
Área Metropolitana de Lisboa	Alentejo	
Romania [8]		
Nord-Vest	Centru	Nord-Est
Sud-Est	Sud - Muntenia	Bucuresti - Ilfov
Sud-Vest Oltenia	Vest	
Serbia [4]		
Beogradski region	Region Vojvodine	Region Sumadije i Zapadne Srbije
Region Juzne i Istocne Srbije		
Sweden [8]		
Stockholm	Östra Mellansverige	Småland med öarna
Sydsverige	Västsverige	Norra Mellansverige
Mellersta Norrland	Övre Norrland	
Slovenia [S]		
Vzhodna Slovenija	Zahodna Slovenija	
Slovakia [4]		
Bratislavský kraj	Západné Slovensko	Stredné Slovensko
Východné Slovensko		
Turkey [26]		
Istanbul	Tekirdag, Edirne, Kirklareli	Balikesir, Çanakkale
Izmir	Aydin, Denizli, Mugla	Manisa, Afyonkarahisar, Kütahya, Usak
Bursa, Eskisehir, Bilecik	Kocaeli, Sakarya, Düzce, Bolu, Yalova	Ankara
Konya, Karaman	Antalya, Isparta, Burdur	Adana, Mersin

(Continued)

NUTS-2 Regions. Continued

Hatay, Kahramanmaras, Osmaniye	Kirikkale, Aksaray, Nigde, Nevsehir, Kirsehir	Kayseri, Sivas, Yozgat
Zonguldak, Karabük, Bartin	Kastamonu, Çankiri, Sinop	Samsun, Tokat, Çorum, Amasya
Trabzon, Ordu, Giresun, Rize, Artvin, Gümüshane	Erzurum, Erzincan, Bayburt	Agri, Kars, Igdir, Ardahan
Malatya, Elazig, Bingöl, Tunceli	Van, Mus, Bitlis, Hakkari	Gaziantep, Adiyaman, Kilis
Sanliurfa, Diyarbakir	Mardin, Batman, Sirnak, Siirt	
United Kingdom [38]		
Tees Valley and Durham	Northumberland and Tyne and Wear	Cumbria
Greater Manchester	Lancashire	Cheshire
Merseyside	East Yorkshire and Northern Lincolnshire	North Yorkshire
South Yorkshire	West Yorkshire	Derbyshire and Nottinghamshire
Leicestershire, Rutland and Northamptonshire	Lincolnshire	Herefordshire, Worcestershire and Warwickshire
Shropshire and Staffordshire	West Midlands	East Anglia
Bedfordshire and Hertfordshire	Essex	Inner London (NUTS 2010)
Outer London (NUTS 2010)	Berkshire, Buckinghamshire and Oxfordshire	Surrey, East and West Sussex
Hampshire and Isle of Wight	Kent	Gloucestershire, Wiltshire and Bristol/Bath area
Dorset and Somerset	Cornwall and Isles of Scilly	Devon
West Wales and The Valleys	East Wales	North Eastern Scotland
Highlands and Islands	Eastern Scotland	West Central Scotland
Southern Scotland	Northern Ireland	
Kosovo [S]		

Notes: Contained in squared brackets is the number of region making up the country. [S] flags all countries made up by single regions. If NUTS-2 display corresponding classification year, it is because they differ from the 2021 version currently adopted (more information here).

A.2 Variables

Summary Statistics

Variable	Description	Source	Min	Max	Mean
Dependent Variable					
Economic Growth	Growth rate of real GDP per capita: deflated by national prices, price base year is 2009	ARDECO/ WiiW	-0.160	0.679	0.011
1. Factor accumulation and convergence					
Initial income	Initial real GDP per capita (in logs): price base year is 2009	ARDECO/ WiiW	6.945	11.436	9.810
Investment Rate	Gross Fixed Capital Formation by GVA	ARDECO/ WiiW/ WDI	0.079	0.748	0.237
2. Demography					
Migration Rate	Migration Rate total	ARDECO/ WDI	-0.042	0.067	0.002
Life Expectancy	Life Expectancy total	Eurostat*/ Nat/ WDI	69.030	85.500	79.950
Fertility Rate	Fertility Rate total	Eurostat/ Nat/ WDI	0.960	3.910	1.639
3. Human capital					
Population with Primary Education	Share of population with primary education or lower levels (ISCED 0-2)	Eurostat*/ ILOSTAT	0.024	0.877	0.285
Population with Intermediate Education	Share of population that has completed secondary or post-secondary non-tertiary education (ISCED 3-4)	Eurostat*/ ILOSTAT	0.087	0.795	0.451
Population with Advanced Education	Share of population that has completed tertiary education, including bachelor's, master's, or doctoral degrees (ISCED 5-8)	Eurostat*/ ILOSTAT	-0.028	0.672	0.263
4. Sectoral structure and employment					
Labour Productivity	Log of GDP per Absolute employment	ARDECO/ Nat/ WiiW	8.098	12.625	10.743
GVA Agriculture	Ratio of the agricultural sector's GVA (NACE A) to the total GVA (current prices),	ARDECO/ WiiW	0.000	0.371	0.041
GVA Industry	Ratio of the industrial sector's GVA (NACE B-E) to the total GVA (current prices)	ARDECO/ WiiW	0.017	0.690	0.215
GVA Construction	Ratio of the construction sector's GVA (NACE F) to the total GVA (current prices)	ARDECO/ WiiW	0.009	0.182	0.062
GVA Services	Ratio of the service sector's GVA (NACE G-N) to the total GVA (current prices)	ARDECO/ WiiW	0.185	0.783	0.457
GVA Public	Ratio of the public sector's GVA (NACE O-U) to the total GVA (current prices)	ARDECO/ WiiW	0.080	0.387	0.225
Employment Rate	Employment Rate total	ARDECO/ WiiW	0.225	0.724	0.519
Unemployment Rate	Unemployment Rate total	ARDECO/ WiiW	0.012	0.475	0.090
NEET Share	Share of Youth Neither in Education, Employment or Training total	Eurostat/ WDI	0.038	0.625	0.160
Economic Activity Rate	Activity rate total	Eurostat/ WiiW	0.293	0.768	0.625
Wage	Log of Monthly Gross Wage in EUR (current prices)	ARDECO/ WiiW	5.109	8.708	7.637

Continued on next page

Table B - Summary Statistics (continued)

Variable	Description	Source	Min	Mean	Max
5. Socio-geographical					
Output Density	Initial output density; GDP (millions)/area (km^2); initial year; price base for GDP is 2009	ARDECO/ WiiW	0.09	12.43	1,004.21
Employment Density	Initial employment density: employed persons (thousands)/area (km^2); initial year	ARDECO/ WiiW	-0.03	0.18	10.78
Population Density	Initial population density: population (thousands)/area (km^2); initial year	ARDECO/ WiiW	0.003	0.34	10.84
Distance to Brussels	Distance to Brussels (km)	Eurostat/ GADM	0	952.78	3,142.71
6. Binary Variables					
CEE	Regions of Bulgaria, Cyprus, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Romania	"1" : 58		"0" : 243	
Candidates	Regions of Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia, Serbia, Turkey, and Moldova.	"1" : 36		"0" : 265	
Capital	Capital city: 0 = region without capital cities; 1 = capital cities	"1" : 37		"0" : 160	
Objective 1	EU Regions eligible for structural funds in areas where GDP per capita is less than 75% of the EU average	"1" : 65		"0" : 236	
Island	Island: 0 = region is not an island; 1 = region is an island	"1" : 12		"0" : 289	
Border	The region shares at least one border with another country: 0 = region is not on the border; 1 = region is a border	"1" : 144		"0" : 157	

Notes: Nat, National Resources included Serbia and Montenegro Statistical Offices. Variables marked with (*) extended their data coverage through ESPON Database. For Binary Variables, dummies of just one representative year were reported with reference year being 2019. Ireland and UK were not treated as islands. Both NUTS-2 regions of London were classified as "Capital". Objective 1 regions were classified from resources available here.

A.3 Top Models

Table A.3: Models with the highest posterior probability: Baseline Setting

	Model 1	**Model 2**	**Model 3**
(Intercept)	0.060***	-0.078***	-0.064**
	(0.014)	(0.020)	(0.021)
GDP per Capita	-0.020***	-0.012***	
	(0.003)	(0.003)	
Labor Productivity	0.009**	0.015***	0.016***
	(0.003)	(0.003)	(0.003)
NEET Share	0.069***		
	(0.011)		
Pop. with Tertiary Edu.	0.054***	0.047***	0.044***
	(0.007)	(0.007)	(0.007)
Investment Rate	0.052***		
	(0.010)		
GVA Construction	-0.158***	-0.177***	-0.134***
	(0.028)	(0.027)	(0.027)
GVA Public	-0.062***		
	(0.010)		
Unemployment Rate	-0.120***	-0.053***	
	(0.012)	(0.011)	
Migration Rate	-0.310***	-0.355***	
	(0.087)	(0.086)	
Candidates		0.043***	0.106***
		(0.003)	(0.006)
CEE		0.025***	-0.010 .
		(0.002)	(0.006)
Capital		-0.009***	-0.004
		(0.002)	(0.003)
Gross Wage			-0.020***
			(0.004)
GVA Industry			0.026***
			(0.008)
Distance from Bruxelles			-0.000***
			(0.000)
Interaction terms			
CEE×Capital			-0.024***
			(0.005)
Candidates×Capital			-0.022***
			(0.005)
Candidates×GVA Industry			-0.149***
			(0.017)
CEE×Pop. with Tertiary Edu.			0.142***
			(0.021)
Candidates×Pop. with Tertiary Edu.			-0.196***
			(0.027)
Observations	3311	3311	3311
Adjusted R^2	0.37	0.39	0.41

Notes: Standard errors are in parentheses. Significance levels are denoted as follows: *** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1.

-chapter

Table A.4: Models with the highest posterior probability: Country Fixed Effects Setting

	Model 1	**Model 2**
(Intercept)	0.094***	0.214***
	(0.027)	(0.041)
GDP per Capita	-0.010***	-0.033***
	(0.002)	(0.004)
NEET Share	0.110***	
	(0.017)	
Labor Productivity		0.012***
		(0.004)
Pop. with Primary Edu.	-0.076***	-0.071***
	(0.011)	(0.010)
GVA Construction	-0.301***	-0.292***
	(0.033)	(0.032)
GVA Public		-0.060***
		(0.016)
Unemployment Rate	-0.080***	
	(0.019)	
Interaction terms		
CEE×Capital		-0.029***
		(0.006)
CEE×GVA Public		0.220***
		(0.052)
Candidates×GVA Services		0.132***
		(0.022)
CEE×GDP per Capita		0.059***
		(0.007)
Candidates×GDP per Capita		-0.039***
		(0.005)
Observations	3311	3311
Adjusted R^2	0.45	0.47

Notes: Standard errors are in parentheses. Significance levels are denoted as follows: *** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1.

Table A.5: Models with the highest posterior probability: Spatial Setting

	Model 1	**Model 2**	**Model 3**
(Intercept)	0.088***	0.088***	-0.001
	(0.023)	(0.023)	(0.015)
GDP per Capita	-0.014***	-0.014***	
	(0.003)	(0.003)	
Labor Productivity	0.013***	0.013***	0.009***
	(0.003)	(0.003)	(0.003)
Gross Wage	-0.013***	-0.013***	-0.020***
	(0.003)	(0.003)	(0.003)
NEET Share	0.082***	0.082***	-0.005
	(0.011)	(0.011)	(0.009)
Life Expectancy	-0.001	-0.001	
	(0.000)	(0.000)	
Pop. with Tertiary Edu.	0.050***	0.050***	0.060***
	(0.007)	(0.007)	(0.007)
GVA Construction	-0.126***	-0.126***	-0.082***
	(0.028)	(0.028)	(0.026)
GVA Industry			0.050***
			(0.007)
Unemployment Rate	-0.134***	-0.134***	
	(0.013)	(0.013)	
Candidates			0.091***
			(0.006)
Interaction terms			
Candidates×GVA Industry			-0.128***
			(0.016)
Candidates×Pop. with Tertiary Edu.			-0.273***
			(0.026)
Observations	3311	3311	3311
Adjusted R^2	0.36	0.36	0.39

Notes: Standard errors are in parentheses. Significance levels are denoted as follows: *** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1.

References

Baker, P., L. Giustozzi, J. Gloser, D. Hanzl-Weiss, E. Merkus, R.-J. Molemaker, and R. Stehrer (2017): "The European Construction Value Chain: Performance, Challenges and Role in the GVC," WIIW Research Report.

Barber, T. (2024): "Balkan clouds over EU enlargement," Financial Times.

Bartlett, W. and I. Prica (2016): "Interdependence between core and peripheries of the European economy: secular stagnation and growth in the Western Balkans," LEQS Paper.

Błażejowski, M., J. Kwiatkowski, and J. Gazda (2019): "Sources of economic growth: A global perspective," Sustainability, 11, 275.

Boldrin, M. and F. Canova (2001): "Inequality and convergence in Europe's regions: reconsidering European regional policies," Economic policy, 16, 206–253.

Brock, W., S. N. Durlauf, and K. D. West (2003): "Policy evaluation in uncertain economic environments," .

Brock, W. A. and S. N. Durlauf (2001): "What have we learned from a decade of empirical research on growth? Growth empirics and reality," The World Bank Economic Review, 15, 229–272.

Brunet, R., J.-C. Boyer, et al. (1989): Les Villes européennes, Rapport pour la DATAR, Délégation à l'Aménagement du Territoire et à l'Action Régionale, Paris: La Documentation Française, under the supervision of Roger Brunet, with the collaboration of Jean-Claude Boyer et al., Groupement d'Intérêt Public RECLUS.

Chipman, H. (1996): "Bayesian variable selection with related predictors," Canadian Journal of Statistics, 24, 17–36.

Cuaresma, J. C., G. Doppelhofer, and M. Feldkircher (2014): "The determinants of economic growth in European regions," Regional Studies, 48, 44–67.

D'Andrea, S. (2022): "Are there any robust determinants of growth in Europe? A Bayesian Model Averaging approach," International Economics, 171, 143–173.

Egri, Z. and I. Lengyel (2024): "Convergence and Catch-Up of the Region Types in the Central and Eastern European Countries," Applied Spatial Analysis and Policy, 17, 393–415.

Feldkircher, M. (2010): "Bayesian Model Averaging (BMA) with uncertain Spatial Effects - A Tutorial," .

Feldkircher, M. and S. Zeugner (2015): "Bayesian Model Averaging Employing Fixed and Flexible Priors: The BMS Package for R," Journal of Statistical Software, 68.

Fernandez, C., E. Ley, and M. F. Steel (2001): "Benchmark priors for Bayesian model averaging," Journal of Econometrics, 100, 381–427.

Ferry, M. and I. McMaster (2013): "Cohesion policy and the evolution of regional policy in Central and Eastern Europe," Europe-Asia Studies, 65, 1502–1528.

George, E. (2007): "Discussion of "Model averaging and model search strategies"," Bayesian Statistics, 6, 175–177.

Gereben, Á. and P. Wruuck (2021): "Towards a new growth model in CESEE: convergence and competitiveness through smart, green and inclusive investment," Tech. rep., EIB Working Papers.

Hinne, M., Q. F. Gronau, D. van den Bergh, and E.-J. Wagenmakers (2020): "A conceptual introduction to Bayesian model averaging," Advances in Methods and Practices in Psychological Science, 3, 200–215.

Hoeting, J. A., D. Madigan, A. E. Raftery, and C. T. Volinsky (1999): "Bayesian model averaging: a tutorial (with comments by M. Clyde, David Draper and EI George, and a rejoinder by the authors," Statistical Science, 14, 382–417.

Kass, R. E. and A. E. Raftery (1995): "Bayes factors," Journal of the American Statistical Association, 90, 773–795.

LeSage, J. P. and O. Parent (2007): "Bayesian model averaging for spatial econometric models," Geographical Analysis, 39, 241–267.

Ley, E. and M. F. Steel (2009): "On the effect of prior assumptions in Bayesian model averaging with applications to growth regression," Journal of Applied Econometrics, 24, 651–674.

Man, G. (2015): "Competition and the growth of nations: International evidence from Bayesian model averaging," Economic Modelling, 51, 491–501.

Maras, M. (2022): "The spillover effect of European Union funds between the regions of the new European Union members," Croatian Review of Economic, Business and Social Statistics, 8, 58–72.

Mischke, J., K. Stokvis, K. Vermeltfoort, and B. Biemans (2024): "Delivering on construction productivity is no longer optional," McKinsey & Company, accessed: October 2024.

Monastiriotis, V. (2011): "Regional growth dynamics in Central and Eastern Europe," LEQS Paper.

Moral-Benito, E. (2012): "Determinants of economic growth: A Bayesian panel data approach," Review of Economics and Statistics, 94, 566–579.

Özyurt, S. and S. Dees (2015): Regional dynamics of economic performance in the EU: To what extent spatial spillovers matter?, 1870, ECB working paper.

Shimbov, B., M. Alguacil, and C. Suárez (2019): "Export structure upgrading and economic growth in the Western Balkan countries," Emerging Markets Finance and Trade, 55, 2185–2210.

Stanišić, N., N. Makojević, and T. ĆURČIĆ (2018): "The EU enlargement and income convergence: Central and Eastern European countries vs. Western Balkan countries," Entrepreneurial Business and Economics Review, 6, 29–41.

Zugravu, B.-G. and A. Ştefania Sava (2014): "Patterns in the Composition of Public Expenditures in CEE Countries," Procedia Economics and Finance, 15, 1047–1054, emerging Markets Queries in Finance and Business.