

04/2026

**Unpacking Regional Heterogeneity
in the EU:
the impact of the ERDF on convergence across
NUTS 2 regions for the 2014-2020 period**

Giulia Porfiri

Master's thesis supervised by Benoît Cyril

Second member of the Jury: Matteo Cavallaro

Master in European Affairs

Policy Stream: Europe in the world

Acknowledgments

This thesis would not have existed in the same form without the guidance of my supervisor, Professor Cyril Benoît, whose feedback sharpened both the analytical framework and my thinking throughout the writing process. I would also like to thank Matteo Cavallaro for agreeing to serve as co-juror and for the time dedicated to reading this research.

My deepest gratitude goes to my family. Their encouragement has been constant and unconditional. They are my source of strength, in this work, and beyond. This thesis is, more than anything, a reflection of their support.

I also warmly thank my friends, spread across Europe, who accompanied me throughout the writing process with long study sessions, late-night conversations about the future and their constant encouragement. Their presence made the difference. I also want to thank Giacomo, whose precious advice and closeness throughout these months meant more than I can properly express here. He has by now become a true expert in cohesion policy.

Writing this thesis has deepened my conviction that regional cohesion is not merely a technical policy question, but one of the most consequential challenges facing the European project. I hope this work is only a first step, and that I will have the opportunity to continue contributing to this field in the years ahead.

Finally, this thesis made occasional use of artificial intelligence tools for paraphrasing and rewording purposes.

List of Abbreviations

ACT	Employment by Economic Activity (variable name)
β (beta)	Beta convergence coefficient
CF	Cohesion Fund
CPI	Cohesion Performance Index
CPR	Common Provisions Regulation
CRII / CRII+	Coronavirus Response Investment Initiative
EAFRD	European Agricultural Fund for Rural Development
EAGGF	European Agricultural Guidance and Guarantee Fund
EDU	Tertiary Educational Attainment (variable name)
EIB	European Investment Bank
EIGE	European Institute for Gender Equality
EMFAF	European Maritime, Fisheries and Aquaculture Fund
EMP	Employment Rate (variable name)
ERDF	European Regional Development Fund
ESF / ESF+	European Social Fund / European Social Fund Plus
ESIF	European Structural and Investment Funds
ESPON	European Spatial Planning Observation Network
EU	European Union
γ (gamma)	ERDF funding intensity coefficient
GDP	Gross Domestic Product
GEN	Gender Employment Gap (variable name)
IJG	Investment for Jobs and Growth
JTF	Just Transition Fund
LIFE	Life Expectancy (variable name)
MFF	Multiannual Financial Framework
NEG	New Economic Geography
NEET	Not in Education, Employment or Training
NUTS	Nomenclature of Territorial Units for Statistics
NUTS 0	Country-level territorial unit
NUTS 2	Second-level territorial unit (primary unit of analysis)
NUTS 3	Third-level territorial unit
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PPS	Purchasing Power Standards
PROD	Labour Productivity (variable name)
QoG	Quality of Government (index)
R&D	Research and Development
R^2	R-squared (coefficient of determination)
RAI	Regional Authority Index
REACT-EU	Recovery Assistance for Cohesion and the Territories of Europe
SAR	Spatial Autoregressive Model

SDM	Spatial Durbin Model
SEA	Single European Act
TECH	High-Technology Employment (variable name)
TEU	Treaty on European Union
TFEU	Treaty on the Functioning of the European Union
UNDP	United Nations Development Programme
WHO	World Health Organisation

List of Figures

Figure 1	Gaps in the Literature vs. Thesis Contributions
Figure 2	Allocation of EU Cohesion Policy Funds by Instrument
Figure 3	Map of EU NUTS 2 Regions (2021 Nomenclature)
Figure 4	Political and Institutional Control Variables
Figure 5	Five-Step Methodological Framework Flowchart
Figure 6	Four-Quadrant Convergence Club Classification Matrix
Figure 7	Overlap of Left-Behind Regions Across Economic Indicators
Figure 8	Temporal Evolution of Convergence Clubs – Economic Dimension
Figure 9	Heatmap of Institutional and Political Coefficients – Economic
Figure 10	Overlap of Left-Behind Regions Across Social Indicators
Figure 11	Temporal Evolution of Convergence Clubs – Social
Figure 12	Heatmap of Institutional and Political Coefficients – Social Dimension
Figure 13	Overlap of Left-Behind Regions Across Employment Indicators
Figure 14	Temporal Evolution of Convergence Clubs – Employment Dimension
Figure 15	Heatmap of Institutional and Political Coefficients – Employment
Figure 16	Choropleth Map – Economic Convergence Trap Score
Figure 17	Choropleth Map – Social Convergence Trap Score
Figure 18	Choropleth Map – Employment Convergence Trap Score

List of Tables

Table 1	Theoretical Perspectives on Regional Convergence and Implications
Table 2	Summary of Empirical Literature on the Effectiveness of EU CP
Table 3	Summary of the Four Research Hypotheses
Table 4	Overview of Key Indicators Across the Three Dimensions
Table 5	Interpretation Matrix of β and γ Coefficient Combinations
Table 6	Absolute β Convergence Results – Economic Dimension
Table 7	Conditional β Convergence Results – Economic Dimension
Table 8	Absolute β Convergence Results – Social Dimension
Table 9	Conditional β Convergence Results – Social Dimension
Table 11	Absolute β Convergence Results – Employment Dimension
Table 12	Conditional β Convergence Results – Employment Dimension
Table 13	Expected vs. Actual Results for Each Research Hypothesis

List of Formulas

Formula 1	Absolute β -Convergence OLS Regression
Formula 2	Conditional β -Convergence OLS Regression with ERDF
Formula 3	Spatial Durbin Model (SDM) for Conditional β -Convergence
Formula 4	Relative Growth Indicator

TABLE OF CONTENTS

Why you should read this thesis	9
---------------------------------------	---

INTRODUCTION	10
---------------------------	----

CHAPTER 1: INTERDISCIPLINARY STATE OF KNOWLEDGE

1.1 Theoretical Foundations of Regional Convergence.....	13
1.1.1 Neoclassical Convergence Theory.....	13
1.1.2 Endogenous Growth Theory.....	14
1.1.3 New Economic Geography Theory.....	14
1.2 Research Gaps in the Literature and Main Contributions of the Thesis.....	16
1.3 Conceptual Foundations of EU Cohesion Policy.....	18
1.3.1 History and Evolution.....	18
1.3.2 Legal Basis of Cohesion Policy.....	19
1.3.3 The Structural Funds.....	19
1.4 Empirical Literature on the Impact of Cohesion Policy.....	21
1.4.1 Evidence of (Economic) Convergence.....	21
1.4.2 Conflicting Evidence and the Multidimensional Gap.....	22
1.4.3 Conditional Effects.....	23

CHAPTER 2: DATA ANALYSIS AND METHODOLOGY

2.1 Research Question and Hypotheses.....	25
2.2 Overview of the Data.....	26
2.2.1 Different Indicators.....	27
2.2.2 ERDF Structural Funds and Population.....	31
2.2.3 Political and Institutional Factors.....	31
2.2.4 Cleaning and Harmonization of the Data.....	33
2.3 Research Design and Methodological Framework.....	33
2.3.1 Identification of the Indicators.....	34
2.3.2 β -Convergence.....	35
2.3.2.1 Accounting for the COVID-19 shock.....	35
2.3.3 Conditional β -Convergence with ERDF Funds and Spatial Dependence.....	36
2.3.4 Cluster Analysis.....	37
2.3.5 Political and Institutional Controls.....	38

CHAPTER 3: RESULTS

3.1 Economic Dimension.....	40
3.1.1 Absolute β -Convergence.....	40
3.1.2 Conditional β -Convergence with ERDF Funds and Spatial Models.....	41
3.1.3 Convergence Clubs.....	41
3.1.4 Political and Institutional Factors.....	43
3.2 Social Dimension.....	44

3.2.1	Absolute β -Convergence.....	44
3.2.2	Conditional β -Convergence with ERDF Funds and Spatial Models.....	44
3.2.3	Convergence Clubs.....	45
3.2.4	Political and Institutional Factors.....	46
3.3	Employment Dimension.....	47
3.3.1	Absolute β -Convergence.....	47
3.3.2	Conditional β -Convergence with ERDF Funds and Spatial Models.....	48
3.3.3	Convergence Clubs.....	49
3.3.4	Political and Institutional Factors.....	50

CHAPTER 4: DISCUSSION AND LIMITATIONS

H1 —	The Convergence Hypothesis.....	52
H2 —	The Multidimensional and Fund-Driven Convergence Hypothesis.....	53
H3 —	The Structural Capacity Hypothesis.....	54
H4 —	The Spatial Spillover Hypothesis.....	55
4.1	Limitations.....	58

CHAPTER 5: CONCLUSION AND POLICY RECOMMENDATIONS

REFERENCES

APPENDICES

Appendix A	Data Sources and Variable Descriptions
Appendix B	Descriptive Statistics for All Nine Indicators (2014–2020)
Appendix C	Full OLS and SDM Regression Output Tables
Appendix D	Spatial Weight Matrix: Construction and Contiguity Maps
Appendix E	NUTS 2 Regional Classification and Territorial Adjustments
Appendix F	Python Code for Data Processing and Econometric Analysis

Why should you read this thesis:

Every year, the European Union invests hundreds of billions of euros in its regions through Cohesion Policy, the largest regional development programme in the world. The implicit promise is straightforward: transfer enough money to lagging territories and they will catch-up with wealthier ones. Yet after decades of funding, a fundamental question remains unanswered: does it actually work, and for whom? This thesis finds an answer more uncomfortable than the official narrative suggests.

The existing literature on Cohesion Policy has two persistent blind spots. It evaluates its effectiveness almost exclusively through GDP per capita, and it assumes that it works similarly for all territories, employing a one-size-fits-all approach. This thesis breaks with both assumptions. By constructing a multidimensional framework of nine indicators across economic, social, and labour market dimensions in a sample of 244 NUTS 2 regions across all 27 EU member states over the 2014–2020 programming period, it offers a comprehensive evaluation of the ERDF. Moreover, by employing a gap analysis, it discovers heterogeneity across Europe, revealing that convergence patterns diverge sharply depending on the dimension examined.

The findings challenge several comfortable assumptions. While economic convergence is confirmed, it is multi-speed: catch-up in the social and structural labour market dimensions is substantially weaker, suggesting that economic growth at the regional level is not translating into broader improvements in welfare. More strikingly, the analysis finds that ERDF transfers are not the engine of the convergence that does occur since endogenous structural factors drive most of it. In some cases, fund allocations are negatively associated with labour productivity growth, pointing to deep inefficiencies in absorption. Perhaps most troublingly, ERDF investments appear to have actively widened the gender employment gap, concentrating their benefits in male-dominated sectors.

The thesis also identifies 36 regions trapped across four or more dimensions simultaneously, concentrated in East Germany, Southern Italy, and French overseas territories, and shows that these development traps are spatially clustered, meaning that the misfortune of lagging regions compounds that of their neighbours. Crucially, clusters differ across dimensions, meaning that economic investment alone is insufficient.

These findings land at a precise moment. The post-2027 reform of Cohesion Policy is currently being negotiated, and narrowing regional GDP gaps are being used by some to argue for reduced funding. This thesis argues that such a conclusion would be premature and misguided because the way they are designed, allocated, and evaluated needs fundamental rethinking. The evidence presented here makes a direct case for a place-based, multidimensional, and spatially aware cohesion framework, one that citizens, policymakers, and researchers cannot afford to ignore.

INTRODUCTION

Defined as “*the glue that keeps Europe together*” (#CohesionAlliance, 2024), Cohesion Policy is the European Union’s main investment policy and world’s largest regional development programme, with a budget of 392 billion euro for the 2021-2027 MFF programming period.

It is a cornerstone of the European integration process in the economic, social and territorial domains, with the objective of reducing disparities among the various territories in the EU Member States (Fundación Yuste, 2025). Its roots can be dated back to the Treaty of Rome, in which Art. 158 highlighted the importance of promoting an “*harmonious development*” of the EU’s regions. After the Treaty of Maastricht, the objective was further consolidated in Art. 174 of the Treaty on the Functioning of the European Union (TFEU) which states that the policy aims at reducing disparities between the different territorial levels of development. Although EU Cohesion Policy remains a largely redistributive policy, with 80% of all Structural and Cohesion Funds transferred from wealthier to poorer regions, its objective is not simple income redistribution (Marzinotto, 2012). Indeed, it aims at fostering economic growth, job creation, business competitiveness, sustainable development, and environmental protection through structural funds (European Commission, 2026).

Cohesion policy, and in particular its main instrument, the Structural Funds, has always attracted significant attention in the literature as a substantial share of the European budget is devoted to this policy. However, despite the effort of scholars and policy-makers in evaluating such policy initiatives, no univocal consensus has been reached so far (Gagliardi and Percoco, 2017). This lack of agreement stems from several limitations in the literature. Firstly, the dominant approach focuses mainly on the economic objectives of cohesion policy, often disregarding the multidimensional objectives of the funds, particularly their effect on social well-being and structural labor market dynamics. Moreover, the results tend to depend on model specification, the indicators selected, most notably GDP per capita, the econometric techniques adopted and the dataset used. Secondly, the majority of the literature assumes a one-size-fits-all model, without accounting for underlying institutional and spatial local conditions, which can dictate a territory’s ability to absorb effectively European funds and drive convergence. More specifically, a major weakness lies in the absence of a distinction between poor regions that are converging and poor regions that are not.

This thesis addresses these problems in several ways. Firstly, it provides a comprehensive pan-European evaluation of the effects of ERDF-funded investments across three distinct dimensions of convergence: economic, social, and employment. By moving beyond the traditional reliance on GDP as an indicator, this research introduces a multidimensional evaluation framework to assess which specific objectives of the structural funds are actually being achieved. Moreover, the thesis is designed to distinguish between lagging regions successfully catching-up and those which remain stuck in a persistent development trap. Finally, it abandons the one-size-fits-all assumption to investigate the pre-existing institutional, political, and spatial conditions that drive the heterogeneity of the ERDF’s effectiveness.

To achieve these contributions, the thesis employs a multi-step quantitative research design. Building on secondary datasets, mainly from Eurostat, the ESPON Database, the Regional Authority Index (RAI), the Comparative Political Data Set, and the Quality of Government (QoG) index, the thesis operationalizes the data using Python. The methodology follows five steps: firstly, it identifies 9 indicators to capture the economic, social and labour market dimension of convergence. Then, it conducts β -convergence regression models to detect structural catch-up trends for both the 2014-2019 and 2014-2020 periods, while also accounting for the exogenous shock of the COVID-19 pandemic. Third, conditional β -convergence regressions are run by incorporating ERDF funding intensity and Spatial Durbin Models (SDM), in order to assess both the effectiveness of the funds and the presence of spatial

spillovers. Fourth, as β -convergence does not capture the heterogeneity of convergence across NUTS2 regions, a gap analysis based on the growth rate and the initial level of each indicator is conducted, categorizing the regions into four distinct convergence clubs: leading regions, stable top regions, catching-up regions and left-behind regions. Finally, categorical control variables are introduced to test how regional decentralization, political orientation, economic openness, and institutional quality influence convergence outcomes.

The thesis presents several key findings. Firstly convergence is present, but it is multi-speed depending on the indicator considered. In particular, the catch-up progress remains slower in the social dimension and in certain aspects of the labour market, such as the gender gap and the sectoral restructuring of the economy. Furthermore, the empirical models demonstrate that the observed convergence is primarily driven by endogenous structural mechanisms rather than by the direct impact of ERDF financial transfers. In fact, the funding is not significant for most of the indicators, and it is even negatively associated with labour productivity convergence, suggesting that funds are often trapped in inefficient local systems suffering from poor absorption capacity. The results also show no significant impact on the social sector, confirming that the ERDF is not the appropriate instrument for human capital formation. Regarding the employment dimension, while the funds appear to have slightly boosted convergence in general employment, they actively widened the gender employment gap, implying that their benefits were concentrated in predominantly male-dominated sectors.

Third, the convergence club analysis makes it possible to divide the regions in four groups, according to their initial level and growth performance for each indicator. This reveals that some regions are lagging across multiple indicators. In particular, 36 regions are classified as left behind in at least four out of nine indicators, account for approximately 14.8% of the NUTS 2 regions sample, and the most persistently trapped regions are concentrated in three areas: East Germany, Southern Italy, and French overseas territories.

At the same time, the spatial concentration of the regions varies depending on the dimension considered. This indicates that intervention focused only on the economic dimension is insufficient to achieve the objectives of Cohesion Policy since different regions experience different forms of disadvantage. Finally, the results show that the convergence is dependent on pre-existing regional characteristics, such as institutional quality, openness of the economy and political orientation of government, as well as by the spatial dimension previously discussed.

This thesis makes several significant contributions to the regional convergence literature. It empirically challenges the neoclassical growth's idea that regions converge due to diminishing returns of capital, demonstrating that financial capital alone does not overcome structural barriers and that policy intervention remains necessary. Furthermore, by integrating spatial econometrics measures, the research empirically validates the concepts of the "Regional Development Trap" and the "New Economic Geography," confirming that convergence and divergence dynamics are structurally tied to negative spatial spillovers and administrative inefficiencies rather than mere underfunding.

The debate on the effectiveness of Structural Funds is particularly relevant in the current period as the allocations under the MFF are being reconsidered in the context of the renegotiation between the European Commission and Member States for the post-2027 reform of Cohesion Policy. In particular, as the differences across NUTS 2 regional GDP per capita were less in 2023 than two decades earlier, some argue that narrower gaps could justify lower funding (Darvas et al., 2026).

The evidence presented in this thesis directly enters the ongoing debate by supporting the idea to move beyond an ex-post evaluation of Cohesion Policy based exclusively on economic outcomes and, on this basis, to strengthen its place-based dimension, that is a tailored approach to integration grounded on the specific characteristics of a region. It also encourages the promotion of cross-regional initiatives capable of generating spatial spillovers and the

coordination of Cohesion Policy with parallel strategies, such as the green and digital transition, in order to foster knowledge spillovers and ensure that no region is left behind. Finally, the findings help manage citizens' expectations, by showing that these policies should not substitute for a national welfare system or an active local labor market policies. Rather, citizens must require their regional authorities to prioritize institutional quality, transparency, and the efficient absorption of funds, since these elements shape the effectiveness of convergence processes.

The thesis is organized as follows. Chapter 1 provides an overview of the main theories underpinning Cohesion Policy and reviews the empirical literature on the relationship between ERDF funding and regional convergence at the NUTS 2 level. It also explains how Cohesion Policy and the Structural Funds operate. The following chapter describes the data analysis and the methodology adopted to generate the results, which are presented in Chapter 3. The results are then discussed, together with an examination of the main limitations of the analysis. Finally, the thesis concludes by outlining the policy implications of the findings and proposing recommendations to improve the design of Cohesion Policy in light of the evidence presented.

CHAPTER 1: INTERDISCIPLINARY STATE OF KNOWLEDGE

Cohesion Policy is the primary investment instrument of the European Union, rooted in its objective of reducing economic, social, and territorial disparities across Member States (EU Commission, 2026). However, while a third of the EU budget for the Multiannual Financial Framework 2021-2027 is devoted to this policy, there is a persistent unresolved debate regarding its effectiveness. The ambiguity stems from the theoretical and methodological choices employed in the evaluation. Therefore, this section provides an overview of the theoretical foundations and empirical evidence on the EU Cohesion Policy, mainly focusing on the role of structural funds in convergence across the economic, social and labour market dimensions.

The chapter is structured as follows. Firstly, it analyzes the three major competing economic theories of regional convergence, namely the Neoclassical Growth Theory, the Endogenous Growth Theory and the New Economic Geography. Then, it identifies the critical research problems and gaps, including an overreliance on the macroeconomic tools of evaluations, in particular on GDP per capita, overlooking the other targeted dimensions of convergence, the lack of a consistent inclusion of spatial and institutional conditions in the framework and the complexities introduced by the COVID-19 pandemic. Third, it outlines the conceptual foundations of Cohesion Policy, including the historical evolution and reforms of the policy, the regulatory framework and the analysis of the structural funds, in particular of the ERDF instrument, in order to ground the analysis in institutional reality. Finally, it synthesises the existing literature on the policy's effectiveness, categorizing findings into evidence of effective convergence, mixed or negative results, and conditional effects.

1.1 THEORETICAL FOUNDATIONS OF REGIONAL CONVERGENCE

To understand the empirical debate on Cohesion Policy, it is essential to trace the economic theories that justify it. The question behind the intellectual foundation of the debate consists in whether regions naturally converge over time or if policy intervention is necessary. Three main theoretical frameworks compete to answer this question and explain regional growth and convergence: Neoclassical Growth Theory (Solow, 1956), Endogenous Growth Theory (Romer, 1986), and New Economic Geography (Krugman, 1991).

1.1.1 Neoclassical Convergence Theory

The dominant approach in the early convergence studies was based on the 1956 Solow-Swann growth model (Solow, 1956). Its central assumption is that there is convergence between regions because, according to the convergence optimism theory, capital is subject to diminishing returns. As a result, it will naturally flow toward capital-scarce regions where returns are higher, meaning that poorer regions will grow faster than richer ones, eventually converging toward a common steady-state level of income (Paas et al, 2006).

The theory identifies different tools of growth, holding that economic growth is rooted in the increase in physical capital, namely in machinery and productive elements, but also in human capital (Butkus et al, 2018) and in the expansion and mobility of labour and factors of production (Abrhám and Vosta, 2020; Costache & Bolos, 2024). In this automatic process, technological progress plays an important role and it can explain differences in disparities and speed of convergence of different economies (Romer, 1990). It is however assumed to be exogenous to the model (Begg, 2010). In this framework, even without intervention, disparities are expected to automatically correct themselves.

However, the model depends on the strong assumptions that markets are perfectly functioning and structural barriers are absent (Armstrong and Taylor, 2000). As this is far from

reality (Begg, 2010), EU Cohesion Policy finds its justification. The latter can help overcome barriers that prevent capital accumulation in less-developed regions, such as inadequate infrastructure, insufficient human capital, or limited access to investment by increasing the rate of investments (Ederveen, 2006). Indeed, Cohesion Policy payments are allocated to the projects intended to create a productive environment, enhance human resources, build infrastructure, raising the amount of physical and human capital, as well as productivity (Butkus et al, 2018).

Despite providing a rationale for intervention, the neoclassical framework has notable limitations. Indeed, investments cannot be considered as a long-term strategy for sustained growth, since diminishing returns to capital eventually reduce the growth effects of additional capital accumulation regardless of how much is injected from the outside (Begg, 2010). Therefore, absolute convergence cannot be assumed for regions with different characteristics, which will converge until their own steady state of the economy (Abrehám and Vosta, 2020) within their own clubs of convergence. They will then struggle to transition to a higher state of development, demonstrating that financial transfers alone cannot permanently lead to convergence (Pieńkowski and Berkowitz, 2015). The theories presented in the following sections looked beyond capital accumulation.

1.1.2 Endogenous Growth Theory

The endogenous growth theory was born as a response to the shortcomings of the neoclassical growth model and its assumptions offer a more suitable framework for analyzing how Cohesion Policy should be designed. Firstly, it criticizes the approach to human capital of the Neoclassical Growth Theory, holding that investment in R&D and education generate great spillovers beyond the region in which they occur. In this way, the theory rejects the law of diminishing returns to capital and abandons the assumption of decreasing returns (Jones, 2002). Secondly, technological change is treated as an endogenous factor to the model itself, generated through innovation, knowledge creation, and human capital formation (Romer, 1990). As a result, long-term economic growth depends on investments in research and development (R&D), education, institutional quality, and knowledge diffusion, as well as on technology development (Jones, 2002). More broadly, endogenous growth theory allows for increasing returns associated with knowledge accumulation, because ideas and innovations can be reused and shared across the economy (Begg, 2010).

From the perspective of EU Cohesion Policy, this theoretical framework carries important implications. Indeed, the structural funds can actively shape economic performance by supporting research infrastructures, education systems, innovation networks, and institutional capacity (Begg, 2010), justifying a shift in cohesion policy from purely redistributive transfers toward strategic investments in knowledge-based regional development (Marzinotto, 2012). A region that receives substantial ERDF transfers concentrated in physical capital, such as infrastructure and construction, may experience economic growth without achieving the structural transformation toward knowledge-intensive activity that drives sustainable long-run convergence. This distinction between income catch-up and structural transformation is central to the analytical framework of this thesis.

Moreover, endogenous growth theory assigns a central role to institutional quality as a determinant of growth outcomes as, where institutions are weak, the returns to private investment are reduced (North, 1990).

1.1.3 New Economic Geography Theory

The New Economic Geography (NEG) is associated with the studies of Paul Krugman (Krugman, 1991). This theory emphasizes the “circular causation” (Myrdal, 1957) and the “positive feedback” (Arthur, 1990), which underpin the logic of agglomeration in a market

economy. Indeed, in this framework location plays an important role in the economic activity of a region as production will tend to concentrate where there is a strong link between supplier and consumer. These demand and supply linkages are further reinforced by market size and economies of scale, which favour the spatial concentration of production (Baldwin and Wyplosz, 2013). Therefore, regions defined by sectoral concentration, availability of skilled labour, the existence of regional clusters, and developed inter-firm linkages are characterized by long-term competitive advantages (Baldwin & Wyplosz, 2013; Krugman, 1995; Abrhám & Vosta, 2020). Conversely, peripheral regions face greater difficulties in attracting production, which may in turn widen disparities between the core and the periphery (Venables, 2005).

Convergence depends on the balance between agglomeration and dispersion forces within an economy. The former consist in the tendency of regions to cluster geographically because proximity reduces transport costs, facilitates knowledge spillovers, and allows access to specialized labour markets and suppliers. The latter, by contrast, arise from costs and infrastructure pressures due to congestion and concentration (Begg, 2010). In the EU integrated market, agglomeration forces prevail (Marzinotto, 2012), leading to regional specialization and an increasing core-periphery gap (Begg, 2010). Krugman (1991) identifies three reasons behind this concentration: firstly, the concentration of several firms in a single location offers a pooled market for workers, ensuring both a lower probability of unemployment for the workers and a lower probability of labor shortage for the investors in industries. Second, localized industries can support the production of non-tradable specialized inputs. And finally, informational spillovers can give clustered firms a better production function than isolated producers (Krugman, 1991).

The NEG theory also introduces two considerations that are absent in the previously presented economic theories. Firstly, the level and speed of development depends largely on initial conditions (Krugman, 1991). Indeed, the level of the individual producer, transport costs, the local movement of productive factors and consumers are largely path-dependent (Paas et al, 2007). Second, the proximity spillovers from dynamic neighbours help lagging regions to converge (Paas et al, 2007).

Therefore, the assumption of “convergence pessimism” (Begg, 2010) justifies the implementation of EU Cohesion Policy in order to counterbalance the impact of market forces working towards divergence (Baldwin and Wyplosz, 2013). Structural funds are indeed necessary in order to prevent excessive spatial concentration of economic activity (Begg 2010). At the same time, it is worth noting that such interventions are not necessarily efficient from the point of view of maximising total aggregate growth (Begg, 2010).

Theory	Convergence Mechanism	Role of Space	Role of Policy	Implications for Cohesion Policy
Neoclassical Growth Theory	Diminishing returns to capital lead poorer regions to grow faster	Space irrelevant	Limited but corrective	Funds accelerate natural convergence through capital accumulation
Endogenous Growth Theory	Knowledge spillovers and innovation generate sustained growth	Indirect role via knowledge diffusion	Strong and strategic	Funds should support R&D, human capital and institutions
New Economic Geography	Agglomeration economies concentrate activity in core regions	Central	Necessary to counter divergence	Funds required to offset core-periphery dynamics and spatial inequality

TABLE 1: Theoretical perspectives on regional convergence and implications for Cohesion Policy, comparing the three competing economic theories across different indicators. Source: table created by the author.

1.2 RESEARCH GAPS IN THE LITERATURE AND MAIN CONTRIBUTIONS OF THE THESIS

Although these three theories differ in the mechanisms through which they explain growth, they all provide important insights into why regional catch-up cannot be taken for granted and why policy intervention may be needed. Neoclassical Growth Theory holds that convergence is possible only within clubs of regions sharing the same institutional and regional characteristics. Endogenous Growth theory highlights the importance of knowledge-based growth, innovation and human capital for long-term growth, while New Economic Geography highlights how agglomeration forces in an integrated market lead to an increase of core-periphery inequalities. Yet, the majority of evaluation studies on the effectiveness of the EU Cohesion Policy tend to overlook these elements, often producing large and inconclusive results.

The limitations presented in this section define both the problem and the contribution of the present thesis. The first major limitation in the existing literature lies in the almost exclusively reliance on GDP per capita as an evaluation indicator of convergence. The choice creates a mismatch between the Cohesion Policy's objectives and what the literature actually tests (Molica et Santos, 2020). Indeed, while article 174 TFEU legally bounds the EU to pursue convergence in the economic, social and labour market dimensions (OECD, 2019), on the other hand, there is no universally accepted definition of the term convergence, only that it is vague, elusive, European, multi-dimensional and difficult to implement and measure (Medeiros et al, 2021). Employing only the GDP as an indicator is inadequate for the multidimensional approach of the policy, as it measures only partially one of its goals, missing part of the picture. As the Endogenous Growth Theory highlighted, a region receiving substantial ERDF transfers for physical infrastructure may experience temporary income catch-up, but without the structural transformation of the economy and knowledge-based investments, long-term convergence will fail (European Commission, 2022).

Therefore, this thesis employs a multidimensional approach, expanding the outcome beyond GDP per capita. Indeed, by analyzing convergence through nine different indicators, it aims at assessing convergence in three different dimensions, namely economic (GDP per capita in PPS, labour productivity, high-technology employment), social (life expectancy, tertiary educational attainment, NEET rate) and labour market (employment rate, gender employment gap, sectoral employment structure). It pivots on the assumption that convergence in one dimension does not necessarily imply convergence across all the dimensions and that focusing on a single outcome risk overstating or understating the success of the policy. This approach allows for the assessment of whether convergence is occurring, in which dimension, at what relative speed and whether economic catch-up is accompanied by a structural development of the economy and of the society.

The second limitation concerns the assumption of a homogenous, pan-European policy effect, where the process of convergence and the effectiveness of the structural funds are treated as constant across the different regions. Most existing studies have estimated a single convergence coefficient through econometric approaches for the whole EU regions sample. In particular, the widely used β -convergence approach developed by Barro and Sala-i-Martin (1992, produces a single aggregate coefficient that cannot distinguish between a situation in which all regions are gradually converging and one in which a portion of regions are catching-up rapidly while another subset is structurally trapped. As a result, it provides limited insight into the territorial heterogeneity of convergence patterns.

Such a one-size-fits-all approach contrasts with the theoretical framework previously displayed. Indeed, Neoclassical Growth theory predicts that convergence is possible only within clubs composed of regions with the same characteristics, while Endogenous Growth Theory assigns a central role to institutional quality and New Economic Geography has highlighted the importance of neighbourhood effects in shaping convergence trajectories. Therefore, further

analysis is needed to uncover the sources of heterogeneity in regional responses to the funds (Le Gallo et al, 2011). Moreover, in line with the first limitation, the dependent variable used in these studies is most often economic growth alone, without considering that the policy operates simultaneously across economic, social and labour-market dimensions.

Even though there have been some recent contributions on the conditional effectiveness of the funds, a systematic investigation of the factors driving this heterogeneity, namely institutional quality, government orientation, regional decentralisation and economic openness, has never been conducted in a comprehensive way. This thesis, therefore, rather than stopping at the estimation of the β -convergence, conducts a club convergence analysis, classifying the 244 NUTS 2 regions in 4 groups according to their initial starting point and to their growth rate. Combined with categorical control variables for the aforementioned factors, this allows a direct and replicable test of which structural conditions are associated with convergence and effectiveness of ERDF funds.

Thirdly, empirical results vary substantially depending on model specification, territorial scale, programming period, type of fund considered, and the econometric strategy employed, making it challenging to draw consistent results from the literature on Cohesion Policy. This thesis directly mitigates this fragmentation by adopting a highly transparent methodological design. The analysis focuses on EU NUTS 2 regions, isolating the 2014–2020 programming period. It also isolates the ERDF and addresses the limitations of standard econometric approaches by employing a Spatial Durbin Model (SDM), which explicitly accounts for spatial dependence, alongside transition matrices to capture patterns of club convergence and regional mobility.

A further limitation concerns the tendency of many studies to aggregate different Structural and Cohesion Funds without isolating the impact of their specific mandates. Indeed, the European Regional Development Fund (ERDF), the European Social Fund (ESF), and the Cohesion Fund (CF), among others, pursue different objective and operate at different territorial levels. Therefore, aggregating them hinders the ability to attribute specific effects to specific instruments. To overcome this bias, this thesis chose to isolate the ERDF allocations. This choice is due to the fact that the ERDF has the largest share of the multiannual cohesion budget, therefore potential policy recommendations might have a bigger impact and, secondly, its territorial articulation at the NUTS 2 level makes it especially suitable for the study of regional convergence across Europe.

A final limitation relates to the distortionary effect of the COVID-19 pandemic on the evaluation of cohesion policy outcomes since the 2014–2020 programming period partially overlaps with the pandemic shock of 2020, which introduced a severe and asymmetric exogenous disruption across EU regions. Including the year 2020 in the estimation may risk confounding the effects of Cohesion Policy with pandemic noise, leading to biased estimates of convergence and fund effectiveness. This issue remains relatively underexplored in the literature. To address this limitation, the thesis adopts a dual period design, comparing the results for the 2014–2019 window, which isolates the pre-pandemic trajectory, and for the 2014–2020 period. This parallel estimation strategy allows to disentangle the structural convergence dynamics from the temporary distortions associated with COVID-19. Where the coefficients differ across the two period, this divergence is interpreted as evidence of pandemic sensitivity rather than as an indication of structural change in convergence patterns.

To conclude, the thesis contributes to the empirical literature on the ex-post evaluation of cohesion policy transfers, and it focuses specifically on the ERDF during the 2014–2020 programming period. It goes beyond the economic dimension, by also considering social and employment outcomes in line with the objectives of the structural fund of Cohesion Policy. It seeks to contribute to the debate on the effectiveness of Cohesion Policy by offering a more multidimensional evaluation of regional convergence in the European Union.

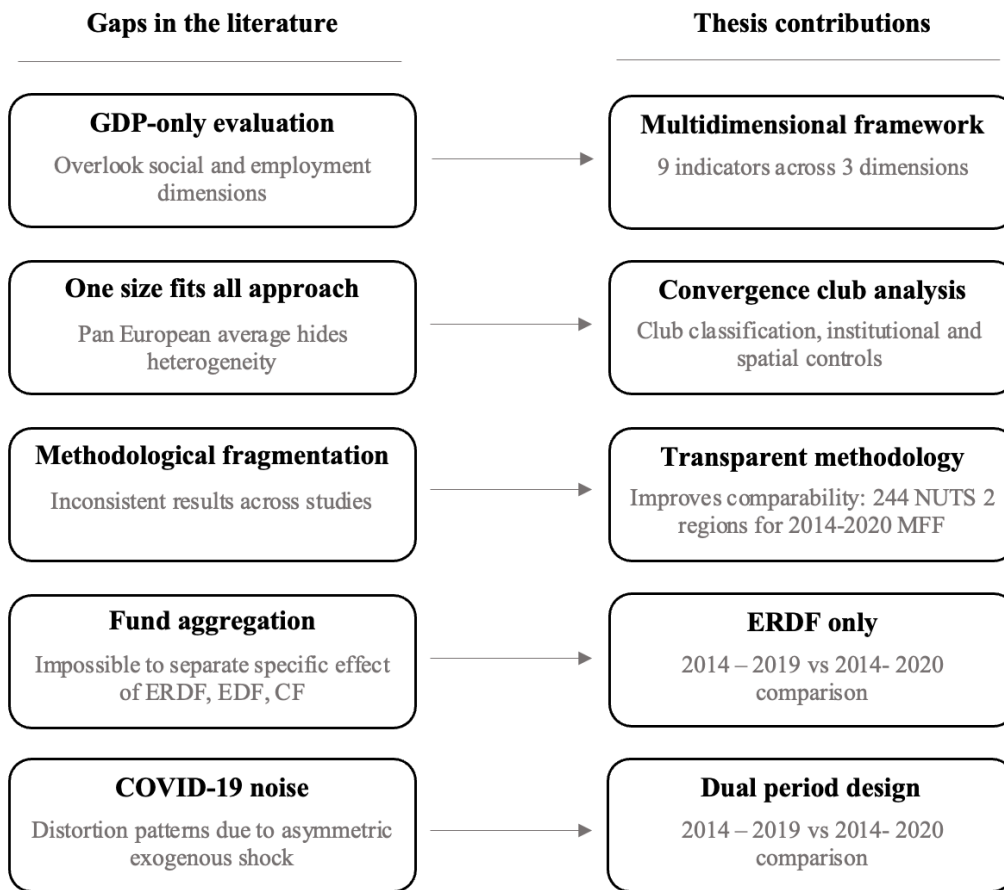


Figure 1: Diagram mapping the five identified gaps in the empirical literature on EU Cohesion Policy to the corresponding methodological contributions of this thesis. Source: figure created by the author.

1.3 CONCEPTUAL FOUNDATIONS OF EU COHESION POLICY

1.3.1 History and evolution

EU Cohesion Policy is one of the major tools of the “European model of redistribution” (Bourdin et al, 2021), aiming at reducing economic, social, and territorial disparities targeting the regions and the cities and focusing on competitiveness, employment, growth and quality of life in general (European Commission, 2026). It did not emerge as a fully formed instrument, but during its evolution it has served broader political and institutional functions, such as the market integration process, EU consensus building and the expansion of EU (Brunazzo, 2016). This historical development was not linear since Member states were reluctant in transferring their national regional competences to the EU.

The first three instruments, the European Investment Bank (EIB) for loans for development projects, the European Social Fund (ESF) for worker training and labour mobility and the European agricultural guarantee fund (EAGGF) for support for rural and agricultural development, were limited (Brunazzo, 2016). In the wake of the 1970s oil crisis and the 1973 enlargement, the policy became more structured with the creation of the European Regional Development Fund (ERDF), whose purpose was to support industry and infrastructure. However, its management remained administered nationally (Brunazzo, 2016). The pivotal transformation occurred with the Single European Act (SEA) in 1986, which introduced the term “cohesion”, and with the 1988 Reform. Following these changes, the budget rose to approximately 30% of the EU total and the development policy transitioned into a fully-fledged EU Cohesion Policy (Brunazzo, 2016).

The Lisbon Strategy (2000) inaugurated a shift of the Policy from a mere focus on economic growth towards an alignment with the EU agenda's objectives (Bourdin et al, 2021). This reform included a stronger coordination between Member States and consequently a centralization of the Policy. The 2014 Reform introduced the European Structural and Investment Funds (ESIF), a new regional classification according to their GDP levels and eleven thematic objectives (Brunazzo, 2016). Finally, a phase of so-called hyper-Lisbonisation has been identified, characterised by the use of Cohesion Policy instruments as a highly flexible and crisis-responsive tool, in particular in the aftermath of the COVID-19 crisis (Bachtler et al, 2013).

1.3.2 Legal basis of Cohesion Policy

The legal foundations of the EU Cohesion policy are embedded in both primary and soft law instruments and have evolved through numerous reforms. The origins of this legal framework are grounded in the preamble of the Treaty of Rome (1957), which recognised the need to reduce economic regional disparities across the Community.

The objectives of the policy are explicitly rooted in the treaties. While Art. 2 of the Treaty of Rome referred to the need for “*a harmonious development of economic activities*”, Art 174 TFEU states that the EU shall strengthen its economic, social and territorial cohesion, in particular reducing disparities within the least favoured regions. The main instruments through which these objectives are pursued, namely the Structural Funds, are highlighted in Art 175 TFEU. In institutional terms, the EU enjoys shared competence on the matter (Art 4 TFEU), while, according to art 177 TFEU, the general implementing regulations for the Structural Funds are adopted through the ordinary legislative procedure. Article 178 TFEU specifically concerns the European Regional Development Fund and provides the legal basis for the adoption of the relevant implementing measures (Kalavros & Georgopoulos, 2013).

This framework is complemented by specific legislative instruments. For the 2014-2020 programming period, which constitutes the temporal scope of the analysis, the primary legislative text is the Common Provisions Regulation 1303/2013 (CPR), which established the common framework for all the operations and functions of the Structural Funds (Arnaoutoglou, 2022). For ERDF funding, the relevant legal basis is Regulation (EU) No 1301/2013 of the European Parliament and of the Council of 17 December 2013 on the European Regional Development Fund and on specific provisions concerning the Investment for growth and jobs goal and repealing Regulation (EC) No 1080/2006.

Finally, the operation architecture of the cohesion funding process rests on four core principles. The principle of Concentration, established in art 18 of the CPR 1303/13, establishes that resources should be focused in areas with greatest needs according to thematic objectives of expenditure. Next, the principle of Programming (art 26 CPR) requires that funds be allocated through multi-annual operational programmes aiming at a specific EU objective. The principle of Partnership (art 5 CPR) mandates structured collaboration between European, national, regional, and local authorities as well as social partners and civil society throughout the programming and implementation cycle. Finally, the principle of Additionality (art 95 CPR) stipulates that EU structural funds shall not replace but complement national public expenditure, preventing member states from substituting EU resources for domestic investment and ensuring that cohesion spending generates genuine additional development benefits rather than simply relieving national budgets (Arnaoutoglou, 2022).

1.3.3 The Structural Funds

The funding of this policy is channelled through different funds (Moreno, 2020). For the 2021-2027 programming period, approximately 392 billion euros were allocated to Cohesion Policy, confirming it as the world's largest regional development programme

(Bourdin et al, 2021). For the 2014-2020 period, the original amount was 351.8 billion, rising to €405 billion including REACT-E (European Commission, 2024).

During the 2014–2020 programming period, Cohesion policy was carried out through five different funds: the European Regional Development Fund (ERDF), which supported balanced regional development, competitiveness and innovation; the European Social Fund (ESF), which focused on employment, social inclusion and human capital; the Cohesion Fund (CF), targeted at Member States whose gross national income per capita was below 90 per cent of the EU average and mainly financing environment and transport infrastructure; the European Agricultural Fund for Rural Development (EAFRD), supporting rural areas and agricultural restructuring; and the European Maritime and Fisheries Fund (EMFF), aimed at the sustainability and competitiveness of the fisheries and maritime sectors. The allocation of resources across the different funds is presented in Figure 2.

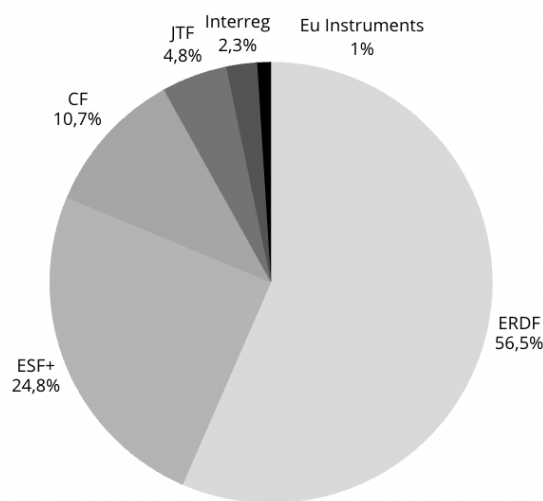


Figure 2: Pie chart showing the percentage allocation of EU Cohesion Policy funds by instrument. Source: figure created by the author, based on data from Cerro, E. (2022)

This thesis focuses specifically on the ERDF during the 2014–2020 programming period. This choice is motivated by several considerations. Firstly, it is the EU's major instrument for regional development, accounting for more than half of the total Cohesion Policy budget, with a total planned amount of 230 billion euros, 99.1% of which has already been paid by December 2024 (EU Commission, 2022). Next, its objectives explicitly cover the three dimensions examined by this thesis, namely the economic, social and labour market. In addition, it operates systematically at the NUTS 2 level, making it directly observable at the territorial scale of the analysis. And finally, ERDF spending data at the regional level are available for the full 2014–2020 period through the ESPON database.

The EU Cohesion Policy operates through multi-annual programming cycles, each defining the strategic priorities, budget allocations, and eligibility rules for the entire period according to defined objectives. In particular, the ERDF for the programming period 2014-2020 supports these 11 thematic objectives:

- (1) strengthening research, technological development and innovation
- (2) enhancing access to, and use and quality of, ICT
- (3) enhancing the competitiveness of SMEs
- (4) supporting the shift towards a low-carbon economy
- (5) promoting climate change adaptation, risk prevention and management

- (6) preserving and protecting the environment
- (7) promoting sustainable transport
- (8) promoting sustainable and quality employment
- (9) promoting social inclusion, combating poverty
- (10) investing in education, training and lifelong learning
- (11) enhancing institutional capacity of public authorities and efficient public administration

As the ERDF basically aims to assist less developed regions, these funds are mainly allocated to EU regions characterized by low development in terms of per capita GDP (below the 75% of the EU average) as well as to regions with declining traditional industries facing structural challenges along other dimensions (McCann, 2015).

More broadly, the functioning of the funds can be divided into four phases: direction, where the overall objectives, budget and regulatory framework are decided; programming, where the defined objectives are translated into concrete plans and programmes in a Partnership Agreement by the Member States, the regional authorities and other stakeholders; implementation, where the planned programmes are put into practice through specific projects and investments by managing authorities through both national and EU funding; and finally monitoring and evaluation. In the 2014–2020 framework, this final stage also included an ex-post evaluation by the Commission under Article 57 of Regulation (EU) No 1303/2013 (Arnaoutoglou, 2014).

1.4 EMPIRICAL LITERATURE ON THE IMPACT OF COHESION POLICY

Given the substantial financial resources devoted to EU Cohesion policy and its long-lasting implementation period (Gagliardi et al, 2017), an extensive share of the literature has emerged to provide an ex-post evaluation of the policy and in particular of the effectiveness of the structural funds (Le Gallo, et al, 2011). However, despite being evaluated since the mid 1970s (Barca, 2009), the empirical evidence has provided mixed, if not contradictory, results (Hagen and Mohl, 2008).

This divergence stems, firstly, from the theoretical debate between the economic theories presented in the first section of this chapter. Indeed, according to the Neoclassical Theory markets should be left free of policy intervention since it leads to efficient market outcomes in the long run. On the contrary, others argue that Cohesion Policy, by attracting investments and by improving structural knowledge-based factors, reduces core-periphery dynamics (Begg, 2010) and creates pre-requisites for growth across the European Union (European Parliament, 2024). Secondly, whether a policy is considered effective or not, depends on its explicit objectives under study and the metrics chosen for evaluation. The following section reviews the empirical evidence and highlights the main inconsistencies in the literature.

1.4.1. Evidence of (economic) convergence

The biggest share of the literature focuses on the economic dimension of convergence, with most econometric studies finding a positive effect of the Structural Funds on regional growth. Montfort (2008), for instance, after reviewing the most frequently employed methods in the literature to analyse convergence, concluded that the EU is a "*convergence machine*", as regional disparities have declined over time. Subsequent research supports this baseline. Crescenzi and Giua (2020) find a positive and significant effect on both regional economic growth and employment, while Di Cataldo and Monastiriotis (2020) assert that this policy was key to reducing disparities among EU regions.

Generally, the studies employing econometric causal methodologies have found more robust effects. In particular, Becker et al (2018), Gagliardi and Percoco (2017) and Crescenzi and Giua (2020) employed a fuzzy RDD regression design and found positive causal effect. Similar conclusions were reached using a sharp RDD approach (Pellegrini et al, 2013). Alternative methodologies also point in the same direction: for instance, Burian and Brčák (2014) use cluster analysis to document a reduction in disparities between core and peripheral Member States.

However, even within studies that show evidence of economic convergence, the benefits of Cohesion Policy appear to be unevenly distributed. Cavenaile and Dubois (2011) found evidence of economic convergence among EU27 countries but emphasize the persistent heterogeneity among Member States as a potential risk for the functioning of the EU and the euro area. Bucur (2012), for example, shows that the new Member States experienced a faster convergence compared to older ones. This finding is supported by Montfort (2008), who highlighted a higher speed of convergence at the EU-27 level relative to the EU-15, and Diaz del Hoyo et al. (2017), who held that Central and Eastern European countries outside the euro area have experienced convergence. Conversely, other studies present highly localized results. Le Gallo et al. (2011) found positive impact of Structural Funds on growth in some regions in the UK, Italy, Spain and Greece, and negative in some regions of Germany, France and Benelux, while Esposti and Busoletti (2008) showed the highest positive impact of Structural Funds on growth in some French regions, and lower, and sometimes even negative, impacts in German, Spanish and Greek regions.

Spatial spillovers further complicate the picture. Bourdin (2019) suggests that the spatial spillovers generated by Cohesion Policy may be stronger in the core than in the periphery. Following the same pattern, some studies have concluded that Cohesion Policy would be more effective if it were more spatially concentrated in the most dynamic regions (Barrios and Strobl, 2009; Fratesi and Perucca, 2014), while De Dominicis (2014), concluding that concentration of Structural Funds in a limited number of regions may enhance growth in the early stages of developments. Furthermore, the impact of the funds is sensitive to external shocks and spatial dynamics. Goecke and Hüther (2016) showed that EU15 countries experienced long-term economic convergence, but that this process slowed and reversed after the financial crisis

Finally, it is important to note that Commission-produced reports tend to generally show positive impacts. However, they tend to be more optimistic than ex-post evaluations, suggesting that the positive picture emerging from official sources should be interpreted with some caution (Costache & Bolos, 2024).

1.4.2. Conflicting Evidence and the multidimensional Gap

Despite the evidence supporting economic growth, a parallel body of literature finds mixed, insignificant, or even negative effects. For example, Mohl and Hagen (2008) find a positive but statistically insignificant impact of Structural Funds on regional growth, while Dall’Erba and Le Gallo (2008) and Rodriguez-Pose and Fratesi (2004) found no significant statistical relationship at all. A similar view is shared by Boldrin and Canova (2000), who argue that Structural Funds were ineffective both in fostering growth and in promoting regional convergence. Ederveen et al. (2006) observed, in general, a negative impact of Structural Funds on growth.

The persistence of contradictory results is frequently attributed to two main factors: uncaptured spatial spillovers and methodological discrepancies. Indeed, with regard to the first issue, in most of the studies, the spatial dimension is completely overlooked. Breidenbach et al. (2019) suggest that spatial spillovers may actually be negative due to intensified competition for scarce production factors among neighbouring regions. With regard to methodology, the literature generally identifies three main convergence hypotheses: absolute, conditional, and club convergence. Absolute convergence assumes that poorer economies grow faster than

richer ones regardless of their structural characteristics. Conditional convergence argues instead that this process occurs only among economies sharing similar structural conditions, such as technology, human capital, institutions, and demographic trends (Mankiw et al, 1995). Club convergence goes one step further, suggesting that economies converge only within groups of countries or regions with similar initial conditions and structural features, each moving towards its own steady-state equilibrium (Ischer and Stirböck, 2004).

Moreover, the literature also distinguishes between two main types of convergence: beta (β) convergence and sigma (σ) convergence. Beta convergence, widely used in empirical studies and adopted in this thesis, refers to a process in which poorer regions grow faster than richer ones, implying a negative relationship between initial income levels and growth rates (Marzinotto, 2012). It can be either absolute, when this relationship holds universally, or conditional, when it applies only among economies with similar structural characteristics (Paas et al, 2007). Sigma convergence, by contrast, measures the evolution of income dispersion over time and occurs when inequalities between regions decline. However, as shown by Quah (1993), β -convergence does not necessarily imply σ -convergence, since faster growth in poorer regions may coexist with persistent or even increasing overall inequality.

A further methodological challenge lies in isolating the effect of Cohesion Policy from other confounding factors, which makes causal identification especially challenging (Pellegrini et al, 2013). More broadly, according to Marzinotto, macroeconomic simulations yield more favourable results than empirical tests and funds may fail to realize their potential due to inefficient allocation or poor investment targeting. The low quality of data on the subject at the regional level further complicated the picture as empirical tests are often compromised by inconsistent methodological choices, varying timeframes, and low-quality data (Mohl & Hagen, 2008).

Finally there is a broader problem in the literature: a highly complex and multidimensional policy has often been evaluated through the narrow lens of GDP alone. This suggests that contradictory findings may stem not only from methodological differences, but also from the tendency to measure the effects of Cohesion Policy through an overly restrictive set of outcomes. For instance, the European Commission finds evidence of economic and social convergence, due in part to Cohesion Policy, with the economic dimension converging more than the social dynamics (European Commission, 2024). This provides the theoretical justification for the Multidimensional Hypothesis (H2) explored in this thesis.

1.4.3. Conditional Effects

To reconcile the conflicting findings of the previous literature, a share of the literature has pivoted toward conditional effectiveness. Di Caro and Fratesi (2021) rejected a one-size-fits-all approach, holding that the long-term macroeconomic effect of the EU policy varies across and within EU countries, with positive and significant effects registered in about 40% of EU regions, and this heterogeneity depends on national and regional contextual factors.

The primary conditioning factor identified in the literature is regional institutional quality. The capacity of the institutions influences the returns of public investments (Rodriguez-Pose and Garcilazo, 2015) and the effectiveness of regional development strategies (European Commission, 2010). In general, regions with better quality of government are less likely to be stuck in a development trap and they are more likely to converge. The level of effectiveness of fund absorption is intrinsically linked to the institutional framework, as well as to labour market characteristics, level of decentralisation, investments and infrastructure development (Moreno, 2020). State intervention may also play an important role, since an efficient utilization of resources depends on an optimal usage of every factor of production and on the ability of public authorities to remove bottlenecks and address structural constraints that prevent the full realization of policy benefits (Burda & Wyplosz, 2008).

Other conditional elements include pre-existing industrial structure, R&D intensity, human capital, science and technology employment and tertiary education (Marzinotto, 2012). Therefore, investments in universities, technological clusters, digital infrastructure, and entrepreneurship ecosystems are seen as key drivers of regional development (Molle, 2006). A paradox is that richer regions tend to perform better in relation to these conditioning factors resulting in cohesion policy being more impactful where it is least needed (Molica & Santos, 2020).

Furthermore, the mixed empirical evidence highlights the fundamental flaw in assuming a one-size-fits-all approach. The reality that simply injecting financial resources into a region does not automatically guarantee structural catch-up suggests that regional convergence is not purely a matter of funding volume. As highlighted in the preceding section, the fact that these funds succeed in some regions but fail in others implies that outcomes are heavily dependent on specific, localized characteristics. This dictates the need to examine the territorial and institutional conditions that moderate policy effectiveness, thereby paving the way for the Structural Capacity Hypothesis (H3) and the Spatial Spillover Hypothesis (H4).

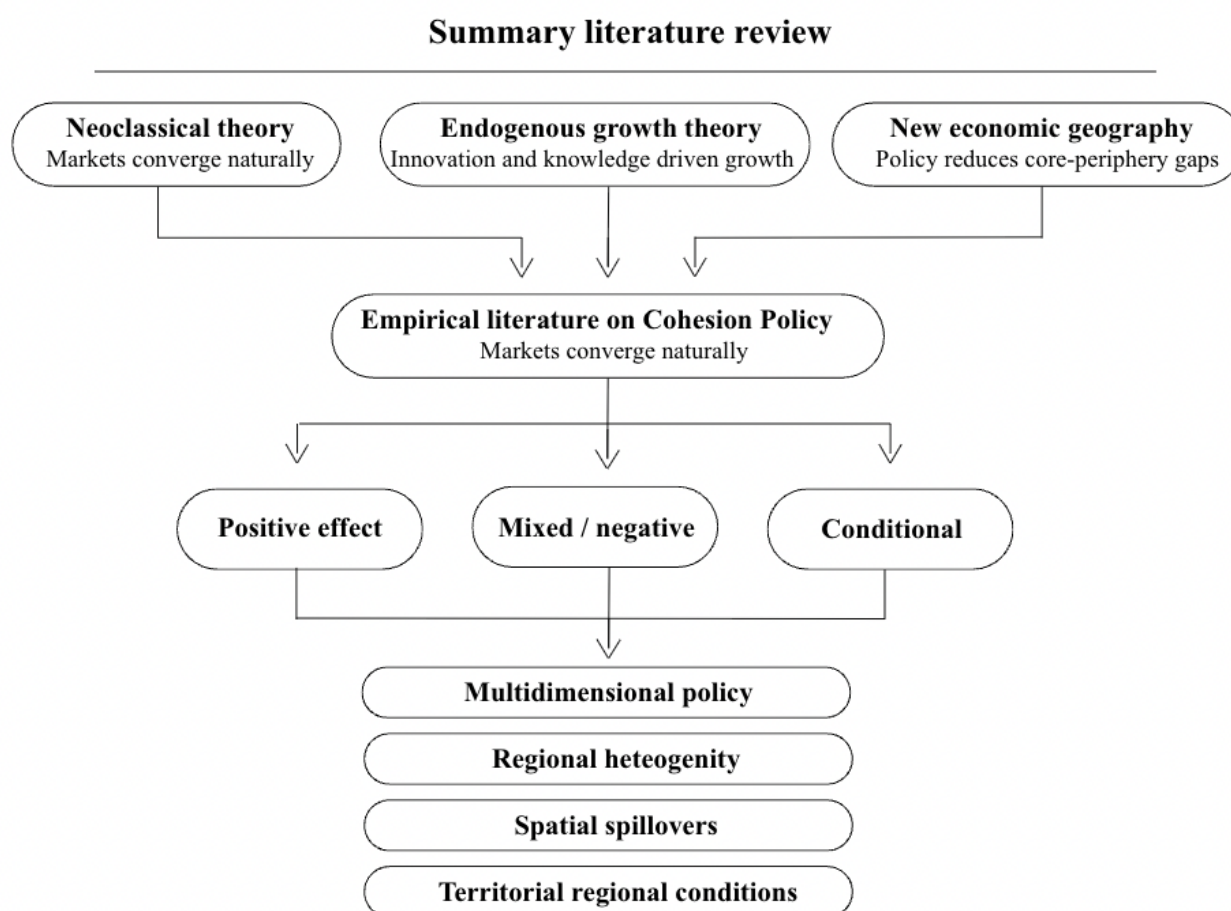


TABLE 2: Summary of the empirical literature on the effectiveness of EU Cohesion Policy, categorized by positive, mixed or inconclusive, and conditional effects on regional convergence. Source: table created by the author.

CHAPTER 2: DATA ANALYSIS AND METHODOLOGY

2.1 Research Question and Hypotheses

In the previous chapter, this research has shown that EU Cohesion Policy is a fundamental pillar of the European Union framework, aiming at reducing regional disparities in accordance with the objectives set out in the Treaties. It has examined the competing economic theories underlying the policy, its functioning and goals, and the existing literature on the matter. As aforementioned, most of the studies assume a one-size-fits-all approach of the policy, without investigating the factors that drive the policy's heterogeneous effectiveness. Moreover, social and labour market dynamics have been neglected in the ex-post analysis of the functioning of the funds, despite being among their stated objectives.

Building on these foundations, the following analysis aims to address the effects of ERDF-funded investments on three dimensions of convergence, economic, social and employment, at the NUTS 2 level during the 2014–2020 MFF programming period, with the primary objective of assessing which regional institutional conditions drive the heterogeneity of the effectiveness of the funds. In doing so, the thesis does not assume a uniform impact of the fund, but instead explicitly considers the role of pre-existing territorial conditions and neighbourhood effects in shaping regional trajectories in order to give policy-relevant insights. To date, no available research appears to offer a similar and comparable pan-European analysis focusing on the effects of the ERDF funds for the three distinct dimensions for the 2014-2020 programming period.

More specifically the objectives of the thesis are three-fold: firstly, assess whether convergence is taking place and check whether it can be attributed to the effects of the funds; secondly, examine the type of convergence observed by comparing outcomes across the economic, social, and employment dimensions, in order to identify which objectives of the funds and of Cohesion Policy are effectively being achieved through ERDF support; and finally investigate whether convergence effects are spatially homogeneous across regions and, if not, what explains the heterogeneity of this convergence.

The analysis adopts a quantitative approach to examine whether convergence occurs, what form it takes, and how it varies across regions. On this basis, the following hypotheses are formulated:

(H1) The Convergence Hypothesis

Higher intensity of ERDF payments is positively associated with a convergence process across indicators within each dimension.

(H2): The Multidimensional Hypothesis

ERDF-funded investments significantly promote economic convergence, while their effects on social and employment convergence are more indirect and mediated by economic performance. This suggests that economic convergence constitutes the primary channel through which improvements in social and labour market outcomes emerge, pointing to a hierarchical relationship among the three dimensions.

(H3): The Structural Capacity Hypothesis

The effectiveness of ERDF-funded investments is conditional on the regions' institutional setting. In particular, the funds are positively correlated with the convergence of regions having a higher degree of decentralization, a higher stability and a more left-wing government.

(H4): The Spatial Spillover Hypothesis

Regional convergence is not an isolated process; it is significantly influenced by geographic proximity. It is expected that the effect of ERDF investments is influenced by spatial spillovers, meaning that a region's economic and social catch-up is positively affected not only by its own development but also by the growth trajectories across the different indicators of its neighbouring regions. Table 3 provides a summary of the hypotheses:

Hypothesis	Short statement	Expected direction
H1	More ERDF lead to more convergence	Positive
H2	ERDF primarily affects economic convergence, which in turn influences social and labour outcomes	Hierarchical
H3	Better institutions, greater economic openness, higher decentralization and left-leaning governments strengthen ERDF effectiveness	Positive conditionality
H4	Neighbouring growth affects regional convergence	Positive spatial effect

TABLE 3: Summary of the four research hypotheses. Source: table created by the author

2.2 Overview of the data

Before presenting the methodology, it is necessary to introduce the available data and outline the characteristics used to assess the level of development of a region. To this end, this study draws on numerous EU NUTS 2 regional panel datasets for the period 2014–2020, including variables capturing the three dimensions of regional development examined by the analysis: economic, social and labour market dynamics, as well as regionalised data on ERDF payments, which makes it possible to investigate the relationship between Cohesion Policy investments and regional convergence patterns.

Eurostat remains one of Europe’s most comprehensive sources of data and this thesis relies extensively on it. However, this source is not without limitations: in particular data for some regions are missing for certain years due to changes in the NUTS nomenclature between 2013 and 2016 and again between 2016 and 2021, since the datasets are not fully harmonized across these revisions. The thesis does not rely on Eurostat alone, but it also relies on other sources of data such as Open Data Platform and the ESPON Database, particularly for information on the funds. While the use of data from different sources broadens the empirical basis of the analysis, it also adds to the complexity, as harmonizing data across different databases is methodologically challenging. These shortcomings will be addressed later in this section.

The analysis covers 27 countries (AT, BE, BG, HR, CY, CZ, DK, EE, FI, FR, DE, EL, HU, IE, IT, LV, LT, LU, MT, NL, PL, PT, RO, SK, SI, ES, SE), subdivided into 244 NUTS 2 regions according to the 2021 nomenclature (Eurostat, 2026). This guarantees full territorial coverage and provides a consistent basis for assessing the effectiveness of the funds across the different indicators grouped into the three distinct, yet interrelated, dimensions of development. The United Kingdom is excluded in order to maintain a cohesive coverage of the territory for the whole period, given the effects of Brexit.



Figure 3: Map of EU NUTS 2 regions according to the 2021 Eurostat nomenclature. Source: figure created by the author.

Most regional-level data are available at the NUTS 2 level. Although NUTS 3 would offer greater precision and broader indicator coverage, European Cohesion Policy is designed, implemented and monitored at the NUTS 2 level, making it the appropriate unit of analysis.

2.2.1 Different indicators

As previously noted, the indicators selected are intended to capture three distinct dimensions of regional convergence, namely economic performance, social development and labour market conditions. Each dimension is measured through three indicators, for a total of nine variables overall, and together they provide a framework for assessing the level of development across NUTS 2 regions. This section introduces each indicator, explains the rationale for its selection, and shows how it is grounded in the existing literature.

Starting with the economic dimension, it is captured through three indicators: GDP per capita measured in Purchasing Power Standards (PPS), labour productivity and people employed in the human resources of high-technology sectors, which serves as a proxy for regional technological capacity. Taken together, these indicators make it possible to measure both the current level of regional economic prosperity and the efficiency and innovative potential of production, therefore providing a broader picture of long-term economic development.

GDP per capita measured in Purchasing Power Standards (PPS) is selected as the first indicator of the economic dimension because it remains the standard benchmark for assessing regional economic convergence (Eurostat, 2025). It captures the average level of economic output produced within a region relative to its population (Eurostat, 2025). Eurostat defines it as “*the central measure of national accounts which summarises the economic position of a country or a region*” (Eurostat, 2026). In this thesis, the indicator is expressed in PPS rather than in nominal terms in order to compensate for price level differences between countries and to allow more meaningful cross-country comparisons (Eurostat, 2026). This choice is also strongly grounded in the literature: GDP per head in PPS is not only the most widely used

indicator in studies of regional convergence, but also the flagship indicator used by international institutions, including EU institutions in the Cohesion reports from 1996 onward (European Commission, 2024), which are documents produced by the European Commission every three years to report on progress towards achieving economic, social and territorial cohesion (Art 175 TFEU). Moreover, it is used by Eurostat as the main indicator in the “Eurostat regional yearbook – 2025”, its annual flagship publication, which provides a detailed picture relating to a broad range of statistical topics across the regions of the EU, EFTA and candidate countries (Eurostat, 2025). For these reasons, GDP per capita in PPS provides the most appropriate starting point for analysing regional convergence, however on its own it cannot fully reflect the broader structural and social dimensions of development.

Labour productivity is selected as the second indicator of the economic dimension because it captures how efficient production inputs are used to produce a level of output in an economy (OECD, 2023). It is measured as the ratio between gross value added and the number of employees. Unlike GDP measured in PPS, labour productivity makes it possible to assess the potential regional long-term growth. For this reason, it is regarded as a key source of economic growth and competitiveness and it serves as an internationally comparable indicator of economic performance (OECD, 2023). The choice is also grounded in the literature. According to the EU Commission, disparities in terms of productivity, even though they are receding, remain high in the EU (EU Commission, 2023). Similarly, OECD evidence confirms the persistent substantial differences across regions since, on average, labour productivity in the worst performing region in an OECD country is 46% lower than labour productivity in the best performing region of the country (OECD, 2023). This slowdown and divergence in productivity growth is problematic for several reasons: it reduces the rate of wage growth that is sustainable in the long term; if low productivity growth rates persist, it may also become harder to service public debts. Moreover, weak productivity performance is directly linked to the risk of regions falling into a “development trap” (Iammarino et al., 2020). Therefore labour productivity is included in the thesis because it reflects a more structural dimension of regional economic convergence. In particular, it indicates the efficient use of labour and reflects the skills and experience of the labour force and also reflects the regional economy’s specific composition of activities as some activities, such as knowledge-intensive sectors tend to be characterised by higher levels of labour productivity (Eurostat, 2026).

Finally, the number of people in the human resources of the sciences and technology sectors is selected as the third indicator. Although this indicator does not measure innovation output directly, such as patents or R&D expenditure, it is used as a proxy for the technological capacity of a region. In the literature, technological development is often identified as a key mechanism of economic convergence. For instance, technology and innovations in the less developed regions are closely linked to convergence as regions that succeed in strengthening their technological base are also more likely to improve their economic performance, while those that fail may end up bearing the costs of the digital transition (European Commission, 2022). More generally, both Neoclassical and Endogenous Growth models state that the level of technology is one of the essential inputs for growth, whether as an exogenous factor that spreads across territories or as an endogenous process linked to knowledge spillovers (Butkus et al., 2018). This indicator is therefore included because, as labour productivity, it captures a structural dimension of regional economic development, showing the capacity of a region to generate knowledge and sustain long-term growth.

Moving to the social dimension, the latter is captured through life expectancy at birth, which indicates the overall health conditions and quality of life of a region, tertiary educational attainment, measured as the share of individuals aged between 25 and 64 holding a tertiary education degree and the number of young people “Not in Education, Employment or Training” (NEET), namely the number of young people who are neither in education nor in work. These indicators provide insight into the short-term convergence in the social dimension as well as

the long-term foundations of human development, since health, education, and youth inclusion are central determinants of a region's future social and economic trajectory.

Life expectancy at birth is defined by the WHO as “*the average number of years that a newborn could expect to live, if he or she were to pass through life exposed to the sex- and age-specific death rates prevailing at the time of his or her birth, for a specific year, in a given country, territory, or geographic area*” (WHO, 2024). It is selected as the first indicator of the social dimension because it provides a comparable measure of population health, meaning quantity of life, as well as of quality of life (OECD, 2025). In the literature, life expectancy is also used as a proxy of health structures (Miladinov, 2020) and, more generally, the United Nations Development Programme includes life expectancy as a component of the Human Development Index, alongside level of education and income, therefore recognising it as one of the core criteria of human development (UNDP, 2026). Life expectancy is therefore included as an indicator as it allows to assess whether regional development is also associated with better health outcomes and improved living conditions.

The level of tertiary education of the population is recognized as a key factor for economic growth and development of an economy, and therefore it is selected as the second indicator of the social dimension. Evidence from the OECD displays that higher education levels generate both economic and social advantages that go beyond the individual itself. Indeed, it is shown that the attainment of a higher education has a positive impact on labour market participation, earnings and on civic engagement (OECD, 2024). In this thesis the indicator is measured as the share of the population aged 25 to 64 holding a tertiary education degree, without distinguishing per gender. The choice of the indicator is consistent with the literature: the European Commission has repeatedly stressed that investment in education and training is necessary to avoid the risk of development traps, as skills remain unevenly distributed across regions and are often concentrated in more developed territories (European Commission, 2022). This is particularly relevant for a study of convergence, because uneven educational attainment reflects persistent differences as education has thus the potential to drive socioeconomic convergence because a highly skilled workforce can be an advantage in terms of productivity, innovation and competitiveness.

The final indicator of the social dimension is the NEET rate, defined here as “*the percentage of the population of a given age group and sex who is not employed and not involved in further education or training*” (EUROSTAT, 2021). The range of population taken in consideration is 18-24. The indicator has been selected as it captures a particularly acute form of social and economic vulnerability among young people. Its relevance is further reinforced by the fact that the reduction of the share of young NEET under the threshold of 9% in 2030 is one of the social objectives of the EU. Yet, in 2024, the EU average was 11.0%, with great differences between territories (Eurostat, 2025). The growth of the NEET group is an even greater problem for society than overall unemployment, as it creates the risk of a lost generation and of long-term exclusion (Bruno et al., 2014). In turn, this affects long-term regional development, as the exclusion of young people can damage future employability and social inclusion. The NEET rate is therefore an essential indicator of convergence as it refers directly to the sustainability of society (Eurofound, 2012).

The third dimension of this thesis focuses on labour market dynamics. Within the 2014-2020 programming period, the ERDF explicitly aimed at increasing employment and improved labour productivity (European Commission, 2026). This dimension is captured through regional overall employment rates, gender employment gap and different employment by economic activity, which allow the analysis to capture both the labour market development level and its structural composition. The regional employment rate is a key indicator to assess the performance of the labour market and the progress towards the EU objectives. It measures the proportion of employed individuals as a percentage of the total working-age population in a region (OECD, 2026). Historically, the focus of regional policy was extended to include

disparities in employment across territories as a consequence of the economic shocks which led to a massive unemployment across the EU (Bachtler et al., 2019). The inclusion of this indicator is therefore important for assessing whether regional labour markets are converging in terms of overall participation and employment capacity.

Secondly, the gender employment gap, defined here as the difference between the employment rates of men and women aged 15-64, is included to assess the quantity and the quality of the labour market development. In the academic literature, gender issues in the academic regional development literature remain underexplored as structural funds are assumed to be gender-neutral. Yet gender inequalities in the labour market may be understood as a form of structural inefficiency that limits both regional competitiveness and social cohesion (Ferrant et al., 2014). Including gender issues within measures of regional performance may facilitate integrating gender mainstreaming in analysis and policy and may facilitate a reduction of horizontal inequalities (Diane Perrons, 2011). The inclusion of this indicator is particularly crucial when comparing the 2014–2019 and 2014–2020 periods. Indeed, the COVID-19 pandemic has been described as a "she-cession," hitting women particularly hard (European Committee of the Regions, 2021) due to their overrepresentation in low-paid sectors as well as in part-time and temporary jobs (Bisello and Mascherini, 2017). By including this indicator, the thesis aims to assess whether structural funds should not be treated as gender-neutral, or whether such an assumption risk obscuring important territorial inequalities (European Commission, 2005),

Finally, the structural composition of the labour market, specifically the division of employment across different economic sectors, constitutes another fundamental factor for regional convergence of the regions. As highlighted by Goecke and Hüther (2016), the regions' endogenous characteristics, such as the relative sizes of the industrial and tertiary sectors, are a driving force in convergence. The underlying rationale is that economic activities are not equally productive in the long term. As previously mentioned, its capacity to drive long-term convergence increasingly depends on its technological intensity and knowledge-intensive services since they foster innovation and create positive spillover effects throughout the local economy. Regions that remain overly reliant on traditional, low value-added manufacturing or agriculture face a higher risk of economic stagnation and may struggle to keep pace with the EU average (Schwab, 2023). Therefore, evaluating employment strictly in aggregate terms is insufficient; it is necessary to examine the structural shifts within the labour market. These three dimensions are analysed separately, while remaining conceptually interconnected. Table 4 provides a summary of the key indicators and their role in the analysis.

Dimension	Indicator	Role in the analysis
Economic	GDP per capita (PPS)	Measures regional prosperity
Economic	Labour productivity	Captures efficiency and competitiveness
Economic	High-technology employment	Proxy for innovation capacity
Social	Life expectancy	Measures quality of life and health
Social	Tertiary education	Proxy for human capital
Social	NEET rate	Captures youth vulnerability
Labour market	Employment rate	Measures labour market performance
Labour market	Gender employment gap	Captures labour market inequality
Labour market	Employment by sector	Captures structural labour composition

TABLE 4: Overview of the key indicators across the three dimensions. Source: table created by the author.

2.2.2 ERDF structural funds and population

One of the aims of the thesis is to assess the effects of the ERDF funding on the three dimensions previously described. Thus, in addition to data on the indicators, information on Cohesion Policy funding is drawn from the dataset “*Historic EU Payments – Annual Timeseries, Regionalised and Modelled*” from the ESPON Database. This dataset includes funding data for all NUTS 2 regions from 2007 onwards. For the purpose of this thesis, only the ERDF payments are retained. The dataset is further restricted to the 2014–2020 programming period and to the EU-27 member states, in line with the temporal scope of the analysis.

Since the objective of the thesis is to capture the intensity of Cohesion Policy support received by each region rather than its absolute amount, the allocations are transformed into a per capita indicator by dividing total regional payments by the population of each region. Population data are extracted from the Eurostat regional demographic statistics, which report annual population figures at the NUTS 2 level. This transformation makes the funding variable more comparable across regions of different sizes and allows the analysis to focus on the relative intensity of support.

The following section introduces the political and institutional variables included to examine whether the effectiveness of the funds varies according to broader structural conditions.

2.2.3 Political and institutional factors

In order to examine whether political and institutional conditions help explain the heterogeneous effectiveness of the funds across regions, four additional indicators are selected. These indicators are analyzed at the national level, since these variables are used to capture the broader institutional and political environment and they are used as control variables in the regressions.

The first indicator is *instdepth*, drawn from the Regional Authority Index (RAI) dataset, which assesses the regional level of decentralization and therefore the extent to which regional governments possess political, fiscal and administrative powers. Developed by Hooghe, Liesbet and Gary Marks in 2016, the RAI is a comparative and longitudinal dataset that measures the degree of authority exercised by regional governments of 95 countries over time since 1950. The current one runs until 2018 and the update will be conducted during 2026 (Gjølstein, 2026). In this thesis, the indicator distinguishes the extent to which regional governments are autonomous rather than merely deconcentrated administrative units. In particular, the variable distinguishes among four broad categories:

- (0) no functioning general-purpose administration at regional level
- (1) deconcentrated, general-purpose, administration
- (2) non-deconcentrated, general-purpose, administration subject to central government veto
- (3) non-deconcentrated, general-purpose, administration not subject to central government veto.

A second control factor is the political orientation of the national government from the Comparative Political Data Set 1960-2023 compiled by Klaus Armingeon, Sarah Engler, Lucas Leemann and David Weisstanner. It is a collection of annual political and institutional data for 36 democratic OECD and EU-member countries for the period of 1960 to 2023 (Armingeon et al., 2025). The variable of interest is *gov_paty*, which classifies cabinet composition on a five-point scale according to the relative weight of left-wing parties in government:

- (1) Hegemony of right-wing (and center) parties (*gov_left1*=0)

- (2) dominance of right-wing (and center) parties ($0 < \text{gov_left1} \leq 33.33$)
- (3) balance of power between left and right ($33.33 < \text{gov_left1} < 66.67$)
- (4) dominance of social-democratic and other left parties ($66.67 \leq \text{gov_left1} < 100$)
- (5) hegemony of social-democratic and other left parties ($\text{gov_left1} = 100$)

Drawn from the same dataset, the third control variable is *openc*, which measures the openness of the economy. It is defined as total trade, meaning the sum of import and export, as a percentage of GDP in current prices. This variable is relevant because, even though trade liberalisation is associated with positive aggregate effects, its benefits are unevenly distributed across territories as some regions are harmed due to external competition. Armstrong and Taylor (2000) notes that international trade is one of the most important factors to reduce the gap in labour productivity and to increase the living standards as the capital moves to poorer regions and increases the economic growth. In this thesis, the variable is grouped into five categories reflecting different levels of openness, ranging from 0 to 4.

Finally, the analysis includes *equi-score_nuts0*, taken from the quality of Government EU Regional Dataset, developed by the Quality of Government Institute at the University of Gothenburg. The dataset contains information on sub-national governance in Europe, gathered through a thirty-four questions survey with more than 34000 respondents on public administration, focusing on concepts related to quality of government, transparency and public administration (University of Gothenburg, 2026). According to the University itself, the quality of government is defined through four variables: rule of law; corruption; quality of the bureaucracy or bureaucratic effectiveness; democracy and the strength of electoral institutions. As demonstrated in the previous paragraph on the literature review, there has been much debate in policy and scholarly circles investigating whether the quality of institutions, in general, and the quality of government, in particular, affects the delivery and efficiency of public investment (Andrés Rodríguez-Pose, Enrique Garcilazo). The variable is grouped into four categories, ranging from the lowest to the highest level of quality of government. Figure 4 provides a summary.

Political and institutional control variables		
Variable	Source	Categories
Decentralization <i>instdepth</i> RAI dataset Hooghe et Marks (2016)	(0) no regional administration (1) deconcentrated (2) subject to central veto (3) autonomous	Low autonomy High autonomy 0 1 2 3 4 ordinal variables
Political orientation <i>gov_party</i> CPDS 1960-2023 Armingeon et al.	(1) right hegemony (2) right dominance (3) balanced (4) left dominance (5) left hegemony	Right Left 1 2 3 4 5 5 ordinal variables
Economic openness <i>openc</i> CPDS 1960-2023 Armingeon et al.	(1) closed economy (2) low openness (3) moderate (4) high openness (5) very high openness	Closed Open 1 2 3 4 5 5 ordinal variables
Institutional quality <i>equi-score_nuts0</i> QoG Institute Univ of Gothenburg	(T.1) lowest quality (T.2) below average (T.3) above average (T.4) highest quality	Weak governance Strong governance T.1 T.2 T.3 T.4 4 ordinal variables

FIGURE 4: Political and institutional control variables used in the analysis. Source: table created by the author.

2.2.4 Cleaning and harmonization of the data

Before presenting the methodology, it is important to address the extensive harmonization of regional data required for this analysis. The European system of NUTS classification underwent several different revisions in 2013, 2016 and 2021 by the Eurostat in order to reflect administrative reforms, demographic changes and territorial reorganisations within Member States (Eurostat, 2026). These regions resulted in changes in regional codes and modified borders, creating inconsistencies when confronting the datasets as the same region may be recorded under different codes depending on the dataset's updates.

The data preparation followed a systematic sequence of steps. First, each dataset was reduced to its essential components, namely a standardized four-character NUTS 2 identifier, the year and the indicator value. Variables were subsequently renamed using a uniform nomenclature to facilitate the regressions and clubs convergence analysis. The data was then restricted to include only EU-27 regions for the period 2014–2020. To ensure consistency across datasets, the GDP per capita in PPS dataset was used as the master reference for regional units. The comparison of the other indicators against this backline, allowed the identification of inconsistencies in regional codes arising from periodic NUTS revisions. Finally, relying on the official correspondence tables between NUTS revisions published by Eurostat, inconsistent regional identifiers were harmonised through several operations to the 2021 NUTS 2 classification framework, consisting in 244 NUTS 2 regions.

This harmonization process involved numerous operations: the direct replacement of outdated codes, the disaggregation of parent regions into their corresponding child regions, the removal of obsolete territorial units and, when necessary, the interpolation or exclusion of problematic regional series. Significant data adjustment was required for Croatia, Portugal and the Netherlands. For Croatia, which joined the European Union in 2013, the NUTS classification for Croatia was revised in 2019 and the country was divided into four regions: Pannonian Croatia (HR02), Adriatic Croatia (HR03), City of Zagreb (HR05), Northern Croatia (HR06). Therefore, the region HR04 was excluded, as the four newly defined territories sufficiently capture data. Portugal experienced complex modifications in its NUTS classification between 2021 and 2024. In particular, the former region PT17, Área Metropolitana de Lisboa, was split into two PT1A, Grande Lisboa, and PT1B, Península de Setúbal, while PT16, Centro, and PT18, Alentejo, were reorganised to create the new NUTS 2 region PT1D, Oeste e Vale do Tejo. To avoid inconsistencies, parent regions were mapped to their corresponding child regions: PT1A was reconstructed using the values of PT17, and PT19 was derived from PT18. The newly delineated regions PT1B, PT1C, and PT1D were ultimately excluded from the analysis due to inconsistent or incomplete time series within the selected framework. In the Netherlands, the revision of the NUTS classification led to the boundary shift between the former NL31 and NL33 and the newly formed NL35 and NL36 regions were reconstructed utilizing the historical values of their parent regions, respectively NL31 and NL33. Additional cleaning steps included the removal of unnecessary variables and the exclusion of specific problematic observations, such as those related to FRY5, which frequently presented incomplete or inconsistent data.

Finally, to conclude the harmonization process, the completeness of the regional time series was systematically verified through Region $\times$ Year pivot tables, allowing for the identification of missing observations or duplicated entries. This procedure ensured that the final dataset used for the empirical analysis contained a consistent set of NUTS 2 regions observed over the entire 2014–2020 programming period.

2.3 Research Design and Methodological Framework

This analysis adopts a multi-step quantitative research design to assess the impact of the ERDF funds on economic, social and employment convergence of EU regions at the NUTS 2 level. Specifically, the research investigates whether the implementation of the funds is

associated with increased convergence and identifies the institutional and political elements that drive the heterogeneous effectiveness across territories. The analysis is grounded in secondary data mainly sourced from the Eurostat and the European Commission's Open Data Portal, with all data processing conducted using Python.

The analytical framework is structured into five sequential phases: (1) indicator selection, (2) β convergence, (3) conditional β convergence, (4) cluster analysis, (5) institutional and political control analysis.

The first part aims to establish the baseline presence of convergence and to isolate the specific effect of the funds, while the second phase transitions into an analysis focusing on regions that fail to converge, aiming to uncover the underlying institutional conditions and spatial dynamics that dictate regional success or stagnation.

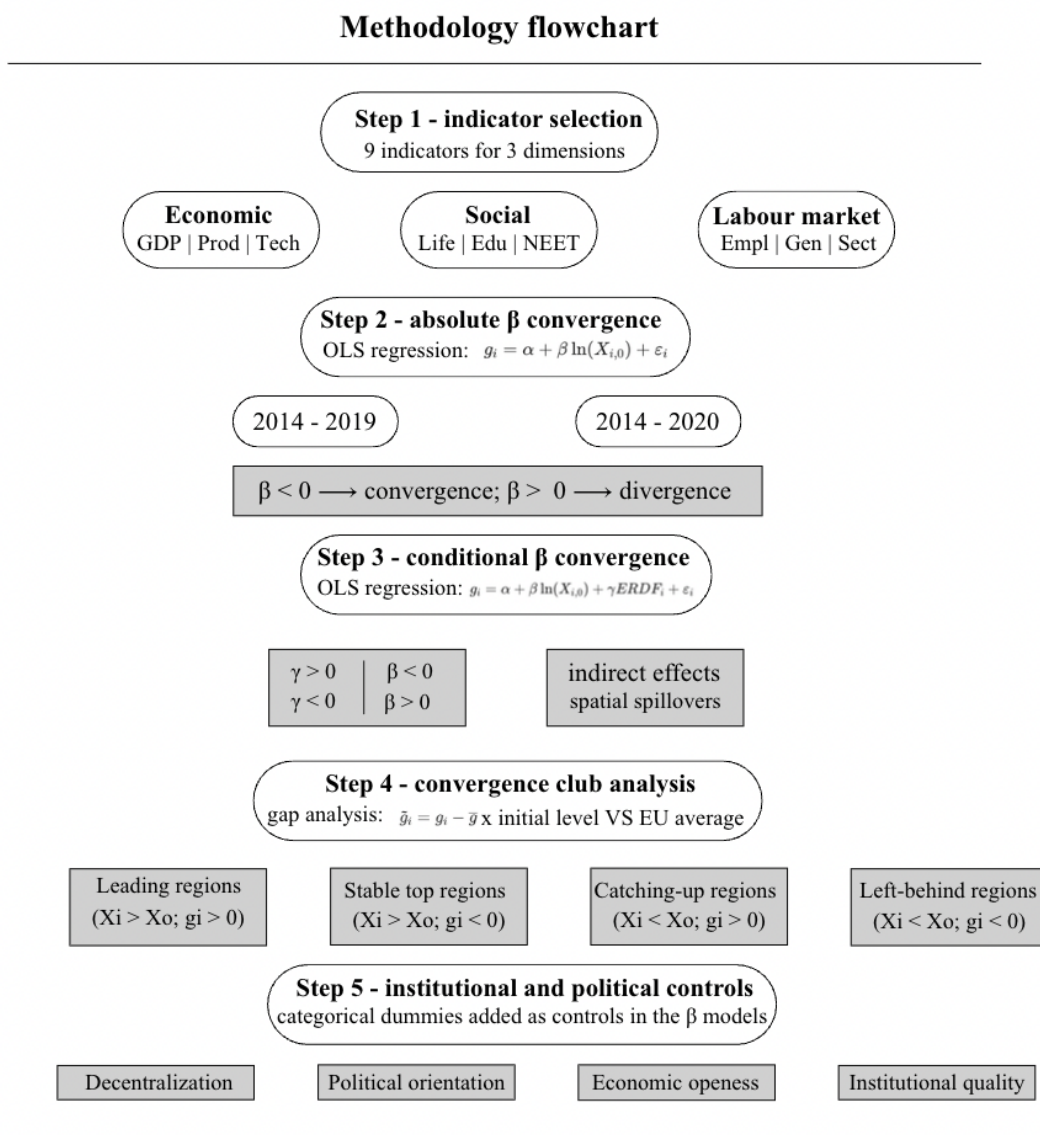


FIGURE 5: Flowchart of the five-step methodological framework adopted. Source: table created by the author.

2.3.1 Identification of the indicators

The first phase of the analysis consists in the selection of specific quantitative indicators to measure regional performance. Building on the literature on regional development previously discussed, this analysis evaluates convergence across three fundamental dimensions: economic performance, social conditions and labour market outcomes. Each dimension is captured by

three regional indicators. The economic dimension, designed to capture the structural productive capacity of regional economies, includes GDP per capita in Purchasing Power Standards (GDP_PPS), labour productivity (PROD), employment in high-technology sectors (TECH). The social dimension is operationalized life expectancy (LIFE), tertiary educational attainment (EDU) and the level of young people who do not work and do not study (NEET). Finally, the labour market dimension allows the analysis to capture both the level and the structure of regional labour markets and it is measured through the regional employment rate (EMP), employment by economic activity (ACT) and the gender employment gap (GEN). Prior to conducting the empirical analysis, all selected indicators underwent data cleaning procedures detailed in the previous section.

2.3.2 β convergence

The second step tests for the presence of absolute β -convergence across the 244 NUTS 2 regions for each of the nine previously defined indicators. The concept of absolute convergence stems from neoclassical theory and it aims to verify whether regions starting from a lower starting point naturally grow at a faster rate than wealthier ones.

The β -convergence is estimated for each region i using the following Ordinary Least Squares regression model:

$$g_i = \alpha + \beta \ln(X_{i,0}) + \varepsilon_i$$

Formula 1: Absolute β -convergence OLS regression. Source: Barro and Sala-i-Martin (1992).

In this specification, g_i represents the annualized growth rate of the selected indicator for region i , obtained by dividing the logarithmic growth of the indicator for the number of years under consideration ($T=5$ for the 2014–2019 period, and $T=6$ when incorporating 2020). The term $\ln(X_{i,0})$ denotes the natural logarithm of the variable's initial level in the base year. The presence and direction of convergence are fundamentally determined by the sign of the estimated β coefficient. A negative value ($\beta < 0$) indicates a catch-up effect, confirming that lagging regions experience higher relative growth rates, while $\beta \geq 0$ suggests an absence of convergence or an ongoing process of regional divergence. The magnitude of the coefficient indicates the speed at which this convergence occurs. Alongside the convergence parameter β , the model estimates the intercept α and the random error term ε .

Computationally, this phase requires specific data restructuring using Python. Each of the nine regional datasets is transformed from a longitudinal panel into a cross-sectional table and after generating the independent variable by extracting the natural logarithm of the base level, the equations are estimated using OLS regression. Post-estimation diagnostics are conducted to evaluate the robustness, in particular the Durbin-Watson statistic is examined to detect spatial spillovers.

2.3.2.1 Accounting for the COVID-19 shock

A core methodological concern in evaluating the 2014–2020 programming period is the asymmetric exogenous shock generated by the COVID-19 pandemic. In 2020, the EU economy contracted by approximately 6% (European Parliament, 2021), with lockdown measures, rising unemployment and severe strain on public healthcare systems disproportionately concentrated in southern Member States such as Italy, France and Spain (Castro Vieira, 2021; Muggenthaler et al., 2021).

Critically for Cohesion Policy, the shock was not uniform: Gräbner et al. (2020) estimate that COVID-19 generated uneven macroeconomic effects across euro area countries, intensifying economic divergence through both supply-chain disruptions and demand shocks

(Abrahám & Vosta, 2020). Martinho (2021) further shows that the pandemic temporarily halted convergence processes in OECD countries, while Lambovska et al. (2021) document a significant deterioration in youth unemployment concentrated in 2020. More broadly, the public health crisis put a tremendous strain on the Member States' and their Regions' healthcare systems, with a bigger burden on Member States that already had high public debt and deficit levels (Coccia and Benati, 2024).

This creates a fundamental methodological dilemma for any ex-post evaluation of cohesion dynamics over the 2014–2020 period. Including 2020 risks contaminating the convergence estimates with pandemic-induced patterns, while excluding it ignores meaningful information about the resilience of regional convergence dynamics under structural shocks. The EU's own policy response through a combination of fiscal flexibility, new financial instruments and adaptations to existing policies further complicates interpretation. The new Coronavirus Response Investment Initiatives (CRII/CRII+) and the Recovery Assistance for Cohesion and the Territories of Europe (REACT-EU) provided liquidity, simplicity and flexibility to the Cohesion Policy actions targeting needs that emerged during the pandemic, but these instruments reduced the resources available for preparing 2021–2027 programmes. Moreover, Cohesion Policy was repurposed as a rapid support instrument rather than as a long-term development tool, sparking some debate since it may come at the expense of the instrument itself (European Committee of the Regions, 2021).

However, very little systematic research on COVID's effect on convergence dynamics has been conducted (Molica & Santos, 2020) and the evidence remains mixed. Therefore, the regression models are estimated in the thesis over two distinct time windows: 2014–2019, which captures convergence dynamics under ordinary policy conditions within the MFF framework, and 2014–2020, which incorporates the pandemic year. Comparing the β coefficients across the two periods allows for a direct assessment of the structural stability of convergence. A significant shift in the sign or magnitude of β would indicate that the pandemic disrupted the pre-existing catch-up trajectory and that the 2020 endpoint cannot be treated as a neutral observation within the programming cycle.

2.3.3 Conditional β -convergence with ERDF funds and spatial dependence

The rationale behind the third step is that absolute convergence fails to identify the impact of the ERDF funds on convergence. To determine if the convergence outcomes identified in the previous section are explicitly associated with the EU Cohesion Policy's tools, the analysis is extended to a conditional β -convergence framework. This approach includes as variables the region's initial level of development, but also additional explanatory factors, respectively the intensity of ERDF investments and the region's spatial position influence.

The conditional convergence model is formally expressed as:

$$g_i = \alpha + \beta \ln(X_{i,0}) + \gamma ERDF_i + \varepsilon_i$$

Formula 2: Conditional β -convergence OLS regression. Source: Barro and Sala-i-Martin (1992).

The key difference between the absolute and the conditional convergence formula lies in the γ parameter, which captures the relationship between ERDF allocations and each indicator's growth. $\gamma > 0$ indicates a positive association between funding and growth, whereas a negative value suggests a negative association. $\gamma = 0$ implies no statistically significant association.

The parameter β continues to capture the level of convergence now controlled for the presence of European funding. The relationship between γ and β provides insights into regional convergence, as detailed in TABLE 5.

β coefficient	γ coefficient	Economic interpretation
$\beta < 0$	$\gamma > 0$	Convergence is actively strengthened by ERDF funds
$\beta < 0$	$\gamma = 0$	Baseline convergence occurs regardless of the funds
$\beta < 0$	$\gamma < 0$	Convergence is hampered by funds (suggesting misallocation or inefficiency)
$\beta = 0$	$\gamma > 0$	Purely policy-driven convergence (growth entirely reliant on funds)
$\beta = 0$	$\gamma = 0$	Complete absence of convergence
$\beta = 0$	$\gamma < 0$	Policy-induced divergence
$\beta > 0$	$\gamma > 0$	Structural divergence that is mitigated by the funds
$\beta > 0$	$\gamma = 0$	Pure divergence, independent of ERDF investments
$\beta > 0$	$\gamma < 0$	Divergence actively amplified by the funds

TABLE 5: Interpretation matrix of β and γ coefficient combinations in the conditional β -convergence model.
Source: table created by the author.

Computationally, the funding intensity variable ($ERDF_i$) is constructed as the cumulative sum of ERDF allocations to a i region over the years, normalized by its initial population in 2014 to ensure comparability. Next, an initial OLS regression is computed, incorporating as the primary explanatory variables both the natural logarithm of the initial level of development ($\ln_X0$) and the natural logarithm of the funding intensity ($\ln_ERDF$).

However, a fundamental limitation of the standard β -convergence model in the regional literature is that it assumes regional independence and therefore ignore spatial interactions. To address this issue, the analysis is extended to include the Spatial Durbin Model (SDM) to account for the spatial spillover effects. The SDM introduces a spatial weight matrix, W , which quantifies the influence of neighbouring regions. Regions sharing a border are given the term $W_{ij} = 1$, otherwise $W_{ij} = 0$. The SDM follows this formula:

$$g = \rho W g + \alpha \iota + \beta \ln(X_0) + \gamma \ln(ERDF) + \theta_1 W \ln(X_0) + \theta_2 W \ln(ERDF) + \varepsilon$$

Formula 3: Spatial Durbin Model (SDM) for conditional β -convergence. Source: LeSage and Pace (2009).

where ρ captures the indicator's growth spillovers deriving from effects of the neighbouring regions, while θ_1 and θ_2 capture exogenous spatial spillovers.

As in the case of absolute convergence, this model is conducted for both 2014-2019 and 2014-2020 periods. This comparative analysis sets the time-period for the following analytical steps analysis. Indeed, if no noticeable change is detected and the coefficient remains stable, the 2014–2019 period can be retained as the main specification as the data are cleaner.

2.3.4 Cluster analysis

The analysis presented so far does not fully address one of the central aims of the thesis, namely the identification of regional heterogeneity in convergence trajectories. Indeed, the β coefficient is a pan-European aggregate indicator, which does not distinguish between rich stable regions and structural lagging regions. Therefore, the methodology shifts from an average-effect framework to a distributional perspective which focuses on how regions' relative positions within the European distribution evolve over time.

For this purpose, a gap analysis is conducted. Firstly, a relative growth indicator (g_i) is computed for each region by subtracting the EU average growth rate from the region's specific growth rate:

$$\tilde{g}_i = g_i - \bar{g}$$

Formula 4: Relative growth indicator formula. Source: author's elaboration.

Then, the region's 2014 initial starting level is compared against the EU average for the same year. By cross-referencing these two relative metrics, NUTS 2 regions are categorized in four distinct performance groups:

1. Leading regions pulling ahead ($X_i > X_o$; $g_i > 0$): regions starting from an above-average position and continue to grow at a faster rate than the EU average.
2. Stable top regions ($X_i > X_o$; $g_i < 0$): regions at an above-average starting position, but experiencing growth rate slower than the EU average
3. Catching-up regions ($X_i < X_o$; $g_i > 0$): less developed regions growing faster than the EU average
4. Left-behind regions ($X_i < X_o$; $g_i < 0$): lagging regions trapped in stagnation scenario

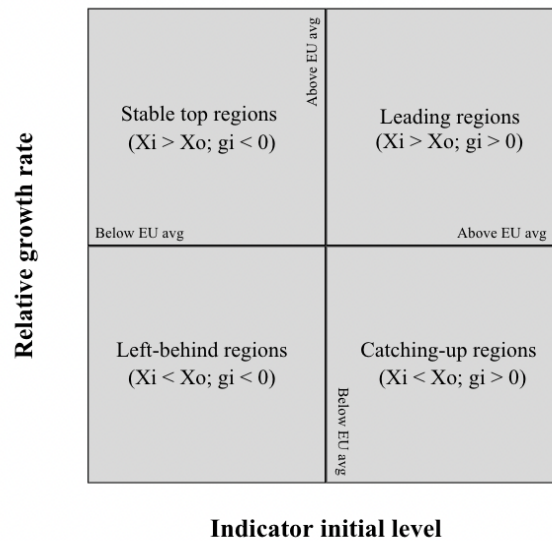


FIGURE 6: Diagram illustrating the four-quadrant classification matrix derived from the club analysis, based on each region's initial indicator level and its relative growth rate. Source: figure created by the author.

2.3.5 Political and Institutional controls

The final step of the analysis shifts from a descriptive analysis of the regional heterogeneous convergence to an explanatory econometric approach, investigating the institutional and political factors that drive this heterogeneity. To achieve this, the analysis leverages the variables detailed in Section 2.2.3, namely the degree of regional decentralization, the political orientation of the national government, the broader administrative quality and finally the openness of the economy.

Methodologically, these criteria are operationalized to conduct an ex-ante clustering analysis. The ordinal categories and quantiles associated with each indicator are transformed

into dummy variables and introduced as categorical control variables within the previously described conditional β convergence and Spatial Durbin regression models.

By introducing these control variables, the model estimates the parameters of convergence conditionally upon the underlying regional governance structures. This econometric strategy ensures that the analysis does not assume a one-size-fits-all impact of EU Cohesion Policy, but investigates which structural, administrative, and political characteristics have an impact on convergence outcomes and effectiveness of ERDF funding.

CHAPTER 3: RESULTS

This chapter presents the findings derived from the methodological framework detailed in the previous section. The results are structured according to the three core dimensions of regional convergence in this thesis: economic performance, social conditions, and labor market dynamics. Within each dimension, the outcomes are examined across the five methodological steps. The next chapter will delve into the discussion of these results, situating them within the broader theoretical and empirical debate.

3.1 Economic dimension

3.1.1 Economic dimension: absolute β convergence

The OSL negative and statistically significant estimations for absolute β convergence reveal a consistent catch-up process across the three indicators of the economic dimension.

Indicator	Period	β Coefficient	Std. Error	R-squared	Durbin-Watson
PPS	2014–2019	−0.0155***	0.0027	0.12	1.04
PPS	2014–2020	−0.015***	0.003	0.094	0.792
PROD	2014–2019	−0.0231***	0.0039	0.131	1.216
PROD	2014–2020	−0.0246***	0.004	0.139	1.016
TECH	2014–2019	−0.0339***	0.0029	0.338	1.602
TECH	2014–2020	−0.0344***	0.0025	0.404	1.221

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 6: Results of absolute β convergence in the economic dimension for the periods 2014–2019 and 2014–2020. Source: table created by the author.

Indeed, for the GDP per capita (PPS), the estimation yields a coefficient of -0.0155, indicating an annual rate of convergence is 1.5% across NUTS 2 regions. When incorporating the year 2020, the magnitude of the coefficient slightly decreases, suggesting that the exogenous shock had a negligible effect on the underlying convergence trajectory. However, the explanatory power of the model indicated by the R^2 decreases from 12% to 9% in the extended 2014–2020 period, implying that initial economic conditions became a weaker predictor of regional growth during the pandemic. Furthermore, the Durbin-Watson value of 1.04 suggests positive spatial autocorrelation among residuals and it hints at spatial clustering.

Labour productivity presents a faster catch-up dynamic, with a β coefficient of -0.0231. Contrary to the trend observed for GDP per capita, the COVID-19 shock seems to slightly accelerate productivity convergence, although the change remains negligible. Here too there is spatial clustering evidenced by the Durbin-Watson value of 1.216 for the 2014–2019 period, which drops to 1.016 when 2020 is included.

Finally, employment in high-technology and science sectors also demonstrates absolute convergence at a faster rate with a β coefficient of -0.0339. The COVID shock is negligible. The Durbin-Watson model result of 1.602 indicates that spatial spillovers exert a comparatively weaker influence than on general macroeconomic output.

3.1.2 Economic dimension: conditional β convergence with ERDF funds and spatial models

Differently from the uniform pattern observed in the absolute convergence estimates, the results obtained across the indicators for conditional β convergence are heterogeneous.

Indicator	Period	β Coefficient	ln_ERDF	W_Growth
PPS	2014–2019	−0.0134***	0.0011	0.5485***
PPS	2014–2020	−0.0198***	−0.0018	–
PROD	2014–2019	−0.0320***	−0.0037***	0.5151***
PROD	2014–2020	−0.0393***	−0.0062***	–
TECH	2014–2019	−0.0079	0.0008	0.0459
TECH	2014–2020	−0.0075	0.0007	–

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 7: Results of conditional β convergence in the economic dimension for the periods 2014–2019 and 2014–2020. Source: table created by the author.

For GDP per capita measured in PPS, the β coefficient remains negative and statistically significant in both periods, with a value of -0.0134, confirming the presence of conditional convergence. However, the coefficient capturing the effects of the funds on convergence is close to zero and statistically insignificant, suggesting that a mere allocation of funds does not automatically convert in accelerated growth. Within the Spatial Durbin Model, the spatial autoregressive coefficient is 0.5485 and highly significant. This indicates substantial positive spatial spillovers, where a 1% increase in the growth of physically contiguous neighbours is associated with an approximate 0.55% growth increase in the region itself.

Labour productivity similarly exhibits conditional β convergence both prior and post the COVID shock, with coefficients of -0.0320 and - 0.0393. These coefficients are larger in magnitude than those observed in the absolute convergence model. However, differently from the PPS estimation, the coefficient representing the effects of the ERDF funds is negative and statistically significant. The spatial lag coefficient remains positive and statistically significant, indicating strong spatial spillovers across regions, with indirect effects exceeding direct effects.

Finally, the results for the science and technology employment differ substantially. β convergence coefficients are statistically insignificant, with values approaching zero in both the baseline and extended periods. The spatial lag coefficient is also statistically insignificant and both direct and indirect effects are negligible.

3.1.3 Economic dimension: convergence clubs

Shifting the focus to the specific territorial units of interest in this thesis, namely structurally lagging regions, the convergence club classification for the economic dimension identifies 61 NUTS 2 regions categorized in this group for GDP per capita (PPS), 58 for labour productivity, and 57 for high-tech employment. These regions are characterized by both low baseline levels of the respective economic indicators and by lower-than-average levels of growth.

Overlap of 'Poor Non-Converging' Regions Across Economic Dimensions

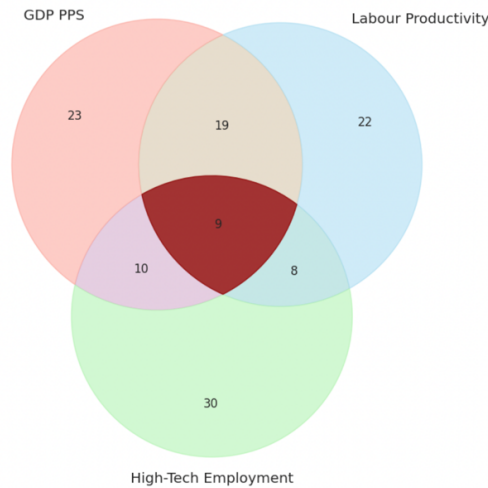


FIGURE 7: Venn diagram showing the overlap of NUTS 2 regions classified as left behind across the three economic indicators Source: figure created by the author.

A cross-indicator examination identifies an overlap within this lagging cohort. Nine regions (E34, DE40, EL43, FRF3, EL65, ES13, ES70, ITF6, ITF4) are simultaneously classified as structurally lagging in all three economic indicators, while 37 that are trapped in two out of three indicators. Detailed geographical considerations regarding the spatial distribution of these specific territories are conducted in Chapter 4.

Temporal Evolution of Convergence Clubs (2014-2020)

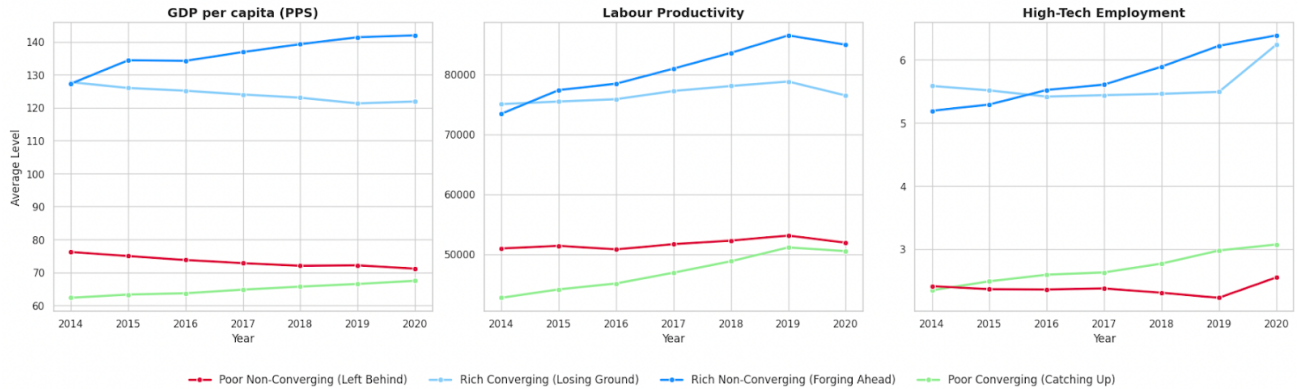


FIGURE 8: Temporal evolution of the average indicator level for the four convergence clubs across the three indicators. Source: figure created by the author.

The temporal evolution of the four identified convergence clubs further confirms these development disparities. For PPS, the lagging converging group exhibits a gradual upward trajectory over time, while the lagging non-converging decline with no recorded periods of growth. Conversely, the leading regions pulling ahead demonstrates the highest increase over the six-year period, further widening the gap with lagging regions. A similar pattern emerges for labour productivity, where the structurally non-converging club remains almost entirely flat. For both PPS and labor productivity, the poor converging regions initiate their trajectories from the lowest absolute levels. Finally, also the high-tech employment indicator shows a divergent trend with the poor converging group displaying moderate growth, while the poor non-converging group stagnates at the lowest recorded levels, contrasted by the pulling ahead club which maintains the strongest upward trajectory.

3.1.4 Economic dimension: political and institutional factors

This section analyses reports the results obtained after introducing political and institutional factors into the β conditional regression for the economic dimension.

For the GDP per capita (PPS) indicator, the inclusion of these variables increases the explanatory power of the model with an R^2 of 51,8%, indicating that the institutional and political context is fundamental to explain the heterogeneous patterns of convergence across regions. Institutional quality demonstrates a significant influence on the regression model. Indeed, the cluster of intermediate-quality displays a positive and statistically significant coefficient (0.0198) relative to the baseline of highly developed governance, while the lowest-quality cluster shows a statistically significant negative effect (-0.0330). The political orientation of the central government has also an effect on PPS growth: balanced cabinets and with a left-leaning majority exert a positive effect, while exclusively left-wing governments show a negative effect. Economic openness remains a driver of success as open regions display a significantly faster growth rate, while the level of decentralization is statistically insignificant, showing only a small negative effect on productivity in moderately centralized economies when the regression includes this control variable alone. Notably, both the absolute β convergence term and the ERDF funding intensity variable become statistically insignificant.

For labour productivity, the effect of institutional quality follows the same trend observed in the PPS indicator, with the lowest-quality cluster's coefficient demonstrating a negative effect of 3%. The political orientation of the government mirrors the trend as well, with a positive effect for balanced and left-majority governments and a negative one effect for exclusively left-wing cabinets. Economic openness remains positively associated with productivity growth. Decentralization becomes statistically significant, with higher levels of decentralization associated with negative coefficients. The beta coefficient remains negative and significant, while the model maintains a robust R^2 of 0.434.

Finally, for high-tech employment, the inclusion of institutional and political variables leads to different results compared to the previous regressions. The coefficients for institutional quality, openness of the economy and decentralization lack statistical significance. However, the political orientation significantly impacts high-tech employment as right-majority (0.0078) and exclusively left-wing governments (0.0103) show a positive association, while balanced cabinets display a negative coefficient (-0.0099). Most notably, the β coefficient becomes negative and statistically significant (-0.0141), indicating convergence dynamics, while the ERDF coefficient remains statistically insignificant and close to zero.

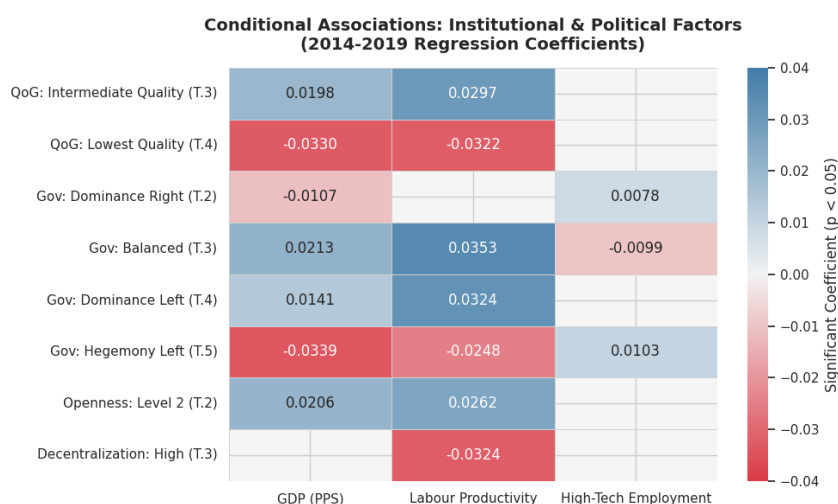


FIGURE 9: Heatmap of statistically significant control regression coefficients from the conditional β -convergence models for the three economic dimension indicators. Source: figure created by the author.

3.2 Social dimension

3.2.1 Social dimension: absolute β convergence

The coefficients of the absolute β convergence for the social dimension, although they remain negative and statistically significant for the three indicators, reveal heterogeneity of speed across the indicators, contrasting with the more uniform trend of the economic dimension.

Indicator	Period	β Coefficient	Std. Error	R-squared	Durbin-Watson
LIFE	2014–2019	−0.007***	0.002	0.049	1.142
LIFE	2014–2020	0.0065**	0.0032	0.017	0.982
EDU	2014–2019	−0.0119***	0.0039	0.038	2.143
EDU	2014–2020	−0.0083**	0.0034	0.024	1.913
NEET	2014–2019	−0.0231***	0.0052	0.076	1.291
NEET	2014–2020	−0.0308***	0.0047	0.154	1.268

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 8: results absolute β convergence in the social dimension for the periods 2014-2019 and 2014-2020. Source: table created by the author.

The life expectancy, the baseline model produces a negative and significant β coefficient of −0.0104, which becomes positive and statistically insignificant when adding the year 2020, suggesting that the convergence process disappears once the COVID-19 shock is taken into account. The Durbin-Watson statistic confirms the presence of spatial autocorrelation, which increases in the extended period. This result is in line with the asymmetric geography of COVID-19 mortality, which affected some areas much more severely than others.

The level of convergence for tertiary education is recorded at 1% per year, but the coefficient drops to −0.0083 when adding the year 2020. In this case, the Durbin–Watson statistic is close to 2 (2.143), indicating only limited residual dependence.

Finally, the NEET rate also exhibits absolute convergence. The β coefficient is negative and statistically significant at −0.023, increasing its magnitude when including the year 2020 at −0.0308, when including 2020, indicating stronger convergence during COVID. The Durbin–Watson statistic with a value of 1.291 indicates the presence of positive spatial autocorrelation.

3.2.2 Social dimension: conditional β convergence with ERDF funds and spatial models

The coefficient of the conditional β convergence broadly follow the trajectories established in the absolute convergence analysis.

Indicator	Period	β Coefficient	ln_ERDF	W_Growth
LIFE	2014–2019	−0.0073***	0.0000	0.6374***
LIFE	2014–2020	0.0028	−0.0001	–
EDU	2014–2019	−0.0109***	−0.0001	0.2515***
EDU	2014–2020	−0.0086***	−0.0008	–
NEET	2014–2019	−0.0145**	−0.0051**	0.4679***
NEET	2014–2020	−0.0254***	−0.0036*	–

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 9: results of conditional β convergence in the social dimension for the periods 2014-2019 and 2014-2020. Source: table created by the author.

For life expectancy, level of tertiary education and level of NEET rate, the conditional β convergence remains negative and statistically significant for the baseline 2014–2019 period. Only in the case of life expectancy does the coefficient lose statistical significance when 2020 is included. However, the magnitude of these coefficients is lower than their levels in the previous absolute regressions, with annual convergence rates measured at 0.7%, 1.09% and 1.45%. The inclusion of the 2020 data reveals a distinct impact on the NEET rate dynamics. Specifically, the COVID-19 shock almost doubled the convergence coefficient to -0.0254, accompanied by an ERDF coefficient reduction to -0.0036.

The Spatial Durbin Models estimated for all three indicators show positive and statistically significant spatial lag coefficients, indicating the presence of strong spatial dependence across the social dimension. Furthermore, the results indicate the indirect spatial effects originating from neighbouring regions are larger than direct effects. However, in the models for tertiary education and the NEET rate, the inclusion of spatial spillovers alters the statistical significance of the β and the ERDF coefficients, rendering them statistically insignificant. Rather than indicating a failure of the model, this result suggests that convergence dynamics and the effects of Cohesion Policy in the social dimension operate to a considerable extent through spatial interactions rather than through purely isolated regional trajectories.

3.2.3 Social dimension: convergence clubs

Across the social dimension, 37 regions fall in the category of structural lagging regions for the indicator life expectancy, 57 for the level of tertiary education and 61 for the NEET rate. These regions combine low initial social conditions with weak or negative improvements over time.

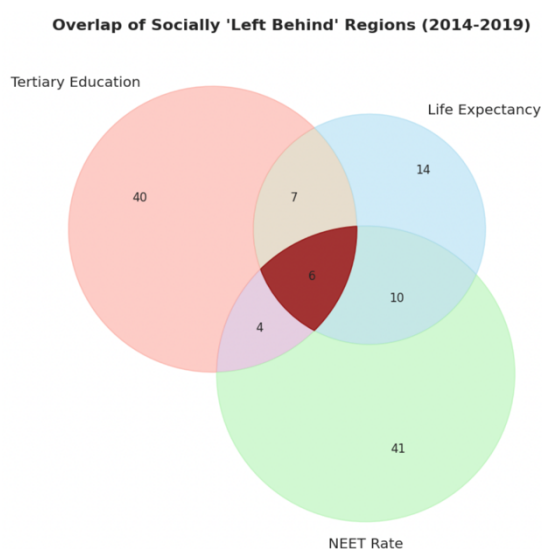


FIGURE 10: Venn diagram showing the overlap of NUTS 2 regions classified as socially "Left Behind" across the three social indicators. Source: figure created by the author.

The overlap across indicators highlights 6 structurally trapped regions in the social dimension: CZ02, DE80, CZ06, DEG0, DEE0, and RO21, while an additional 21 regions are trapped in two out of three indicators.

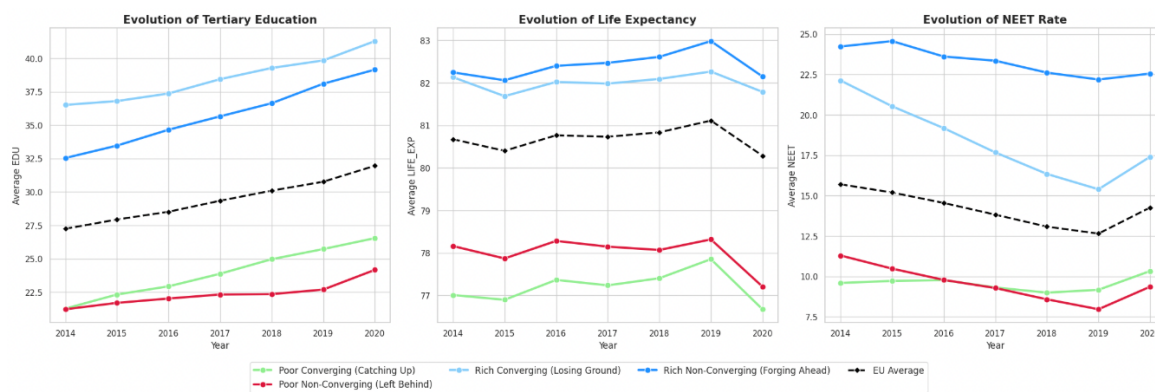


FIGURE 11: Temporal evolution of the average indicator level for the four convergence clubs across the three social indicators. Source: figure created by the author.

The dynamic evolution of the four convergence clubs confirms these patterns of non-convergence for the structural lagging club. Indeed, in the tertiary education indicator, the leading, stable-top and catching-up show an upward trajectory, whereas the structurally lagging group grows at a much slower pace and remains almost entirely flat throughout the primary period of analysis, with a marginal upward trend only in the year 2020.

For life expectancy, while the absolute gap between the above EU average regions and the below EU average regions remains substantial, the temporal trajectories are less divergent than in the other social indicators. Nevertheless, the structural lagging club is the only cohort to exhibit a marginal downward trend over the observed period. A notable feature of this indicator is the sharp, synchronized decline experienced by all clubs in 2019, which was steeper for the poor regions.

Finally, in the NEET rate, the catching-up group and the left-behind group follow radically different trajectories, as the former displays a slightly upward-sloping trajectory, while the latter suffers from a steep and continuous divergence. The dynamics of the better-performing group requires attention as it records a substantial decline, suggesting that the observed statistical convergence is largely driven by a deterioration of conditions for rich regions rather than a uniform improvement across the Union.

Overall, the convergence club results for the social dimension indicate persistent disparities between groups of regions, with a subset of territories systematically lagging behind across multiple social indicators and limited convergence over time.

3.2.4 Social dimension: political and institutional factors

The inclusion of political and institutional variables alters the conditional β -convergence models for the social dimension, though the impact is highly heterogeneous across the three indicators.

For life expectancy, the introduction of structural controls reveals a limited impact of institutional and political factors as the majority of the variables are statistically insignificant. However, when political factors are considered in isolation, the category corresponding to balanced governments and the category capturing left-party hegemony display statistically significant, though very small, negative effects. Economic openness which has a positive relationship with convergence only for the period 2014-2019. Once these controls are introduced the β convergence coefficient loses its statistical significance, while the ERDF coefficient becomes positive and statistically significant (0.0002), indicating a small positive association with improvements in health outcomes.

In the case of tertiary education, institutional quality and decentralization variables are statistically insignificant. By contrast, a balanced government configuration is associated with

a negative effect, while a predominance of the right shows a small positive effect when considered in isolation. Economic openness, however, is positively and statistically significantly associated with education growth. While the ERDF coefficient is statistically insignificant, the β coefficient remains negative and statistically significant, confirming that conditional convergence in education persists even when accounting for the institutional environment.

For the NEET rate, institutional quality variables emerge as determinants of convergence for the indicator, as higher quality clusters show negative coefficients compared with the performance baseline. Furthermore, political orientation variables also play a role, with left-leaning and left-hegemonic alignments displaying negative effects. Economic openness and decentralization variables are statistically insignificant, as well as the β coefficient and the ERDF variable upon the introduction of these control variables. A moderately open economy, when considered in isolation, has a slightly negative effect.

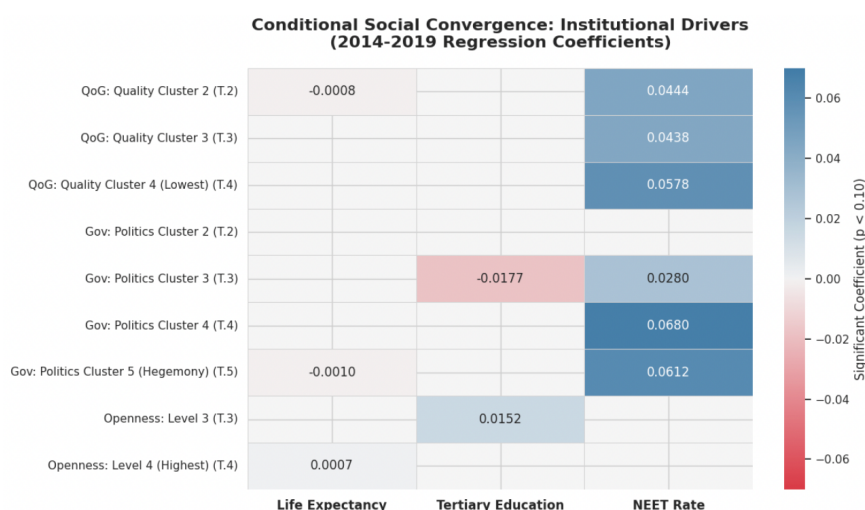


FIGURE 12: Heatmap of statistically significant control regression coefficients from the conditional β -convergence models for the three social dimension indicators Source: figure created by the author.

3.3 Employment dimension

3.3.1 Employment dimension: absolute beta convergence

The absolute β -convergence results for the employment dimension provide heterogeneous evidence of convergence across the three indicators of the sector.

Indicator	Period	β Coefficient	Std. Error	R-squared	Durbin-Watson
EMPL	2014–2019	−0.0249***	0.004	0.146	1.65
EMPL	2014–2020	−0.0227***	0.003	0.152	1.68
GEND	2014–2019	−0.0326***	0.008	0.074	1.72
GEND	2014–2020	−0.0262***	0.007	0.055	1.7
KNOW	2015–2019	−0.0011	0.001	0.005	1.509
KNOW	2015–2020	−0.0008	0.001	0.003	1.615

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 10: results of absolute β convergence in the employment dimension for the periods 2014-2019 and 2014-2020. Source: table created by the author.

Firstly, the employment rate indicator displays clear evidence of convergence with a negative and highly significant coefficient of -0.0251 . This dynamic holds even when including the year 2020, with only a negligible decrease in the coefficient's magnitude. In this regression, it is important to notice that the Durbin–Watson statistic is heavily below 2, indicating strongly that employment growth is heavily influenced by spatial autocorrelation.

The gender employment gap indicator exhibits the strongest absolute β convergence, with a statistically significant value of -0.0319 , suggesting a faster narrowing of the gender gap rather than overall labour market gaps. The Durbin–Watson statistic is close to 2, suggesting limited spatial autocorrelation.

Finally, the analysis of employment in knowledge-intensive services reveals a total absence of systematic convergence, with all coefficients not statistically significant.

3.3.2 Employment dimension: conditional beta convergence with ERDF funds and spatial models

This section explores the relationship between ERDF funding, spatial spillovers, and labor market outcomes by applying conditional β convergence and Spatial Durbin Models (SDM) to the employment dimension.

Indicator	Period	ln_X0	ln_ERDF	W_Growth
EMPL	2014–19	-0.0167^{***}	0.0018^{***}	0.5724^{***}
EMPL	2014–20	-0.0145^{***}	0.0018^{***}	–
GEND	2014–19	-0.0413^{***}	0.0152^{***}	-0.0079
GEND	2014–20	-0.0335^{**}	0.0114^{***}	–
KNOW	2014–19	-0.0019	0.0002	0.4863^{***}
KNOW	2014–20	-0.0017	-0.0001	–

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

TABLE 11: results of conditional β convergence in the employment dimension for the periods 2014-2019 and 2014-2020. Source: table created by the author.

The results for the employment rate's β -coefficient confirm the persistence of statistically significant convergence as it remains negative and statistically significant. Cohesion Policy seems to be playing a role in these dynamics as the coefficient of the ERDF fund's effect is positive and statistically significant, though its small magnitude suggests a modest overall contribution to regional employment growth. In the spatial model, the spatial lag coefficient is positive and statistically significant (0.57237), indicating strong spatial dependence across regional labour markets. Notably, the indirect effects are larger than the direct effects. While both the β and the ERDF coefficients remain statistically significant in the spatial specification, their magnitude decreases in half.

The gender employment gap indicator shows convergence, with a negative and statistically significant β coefficient, even though the magnitude diminishes when including the year 2020, mirroring the trend of the absolute β convergence regression. It is worth noting that the ERDF coefficient is negative and statistically significant, indicating that higher funding is associated with a widening of the gender gap. Unlike general employment, the spatial lag coefficient for the gender gap is statistically insignificant, suggesting weak spatial dependence.

Finally, the sectoral employment model does not display conditional convergence as the β and ERDF coefficients are statistically insignificant, indicating that neither initial conditions nor cohesion funds are currently driving a catch-up process in high-value service sectors. However, the spatial lag coefficient is positive and statistically significant, indicating that knowledge-intensive employment is still subject to strong spatial dependence

3.3.3 Employment dimension: convergence clubs

The cluster analysis reveals a stagnant group of regions in the employment dimension. Indeed, the structurally lagging club for the employment rate indicator consists of 46 regions, while 78 for the tertiary education indicator and 82 in the sectoral employment structure. These regions are characterized by low initial performance of the indicator and a negative growth dynamic.

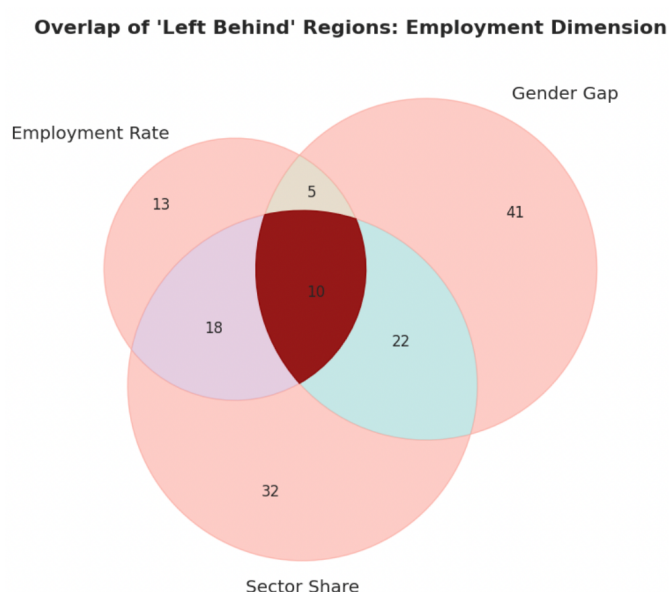


FIGURE 13: Venn diagram showing the overlap of NUTS 2 regions classified as "Left Behind" across the three employment dimension indicators. Source: figure created by the author.

The structural nature of this stagnation is most evident in the overlap across indicators. The group consisting of trapped regions across the three indicators is composed of 10 regions (BE22, DE80, BE35, FI1C, FRY2, FRE2, FRD2, FRI3, ITC2, FRY4), while other 45 are trapped in two out of three indicators.

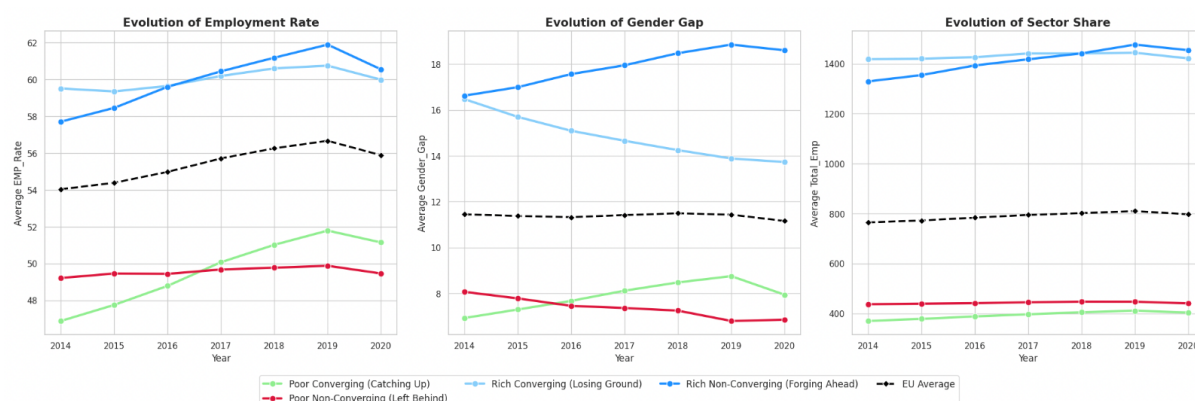


FIGURE 14: Temporal evolution of the average indicator level for the four convergence clubs across the three employment dimension indicators. Source: figure created by the author.

The temporal variation of these indicators displays a profound divergence of trends across the four clusters. In the employment rate, while the previous analysis revealed a pan-European convergence across NUTS 2 regions in the EU, the benefits were not distributed evenly among them. The structurally lagging group is the only one to maintain a consistently flat, low-level trajectory, while the others exhibit upward-sloping trajectories, with the rich non-converging group recording the highest and most sustained growth path, increasing the absolute gap in employment participation.

A similar pattern is found for the gender employment gap indicator and the poor non converging remain below the EU average with a slightly downward-sloping curve, indicating worsening relative position, whereas the rich non-converging and poor converging groups display more favourable trends.

Finally, in the sectoral employment model, divergence is particularly pronounced. While the trajectories for most clubs are relatively flat, the pulling ahead group is the only one displaying a distinct upward trend. It is worth noting the wide gap between the richer and poorer groups throughout the period. Overall, the convergence club analysis for the employment dimension indicates persistent labour market disparities.

3.3.4 Employment dimension: political and institutional factors

This section analyses the inclusion of political and institutional variables in the labour market dimension.

For the employment rate, the analysis shows that general labor participation is deeply sensitive to the political ecosystem. Indeed, baseline political configuration, consisting in a right-hegemony cabinet, possesses a severe comparative advantage in fostering employment, leaving all other ideological or political configurations at a distinct structural disadvantage in the labor market, as evidenced by the negative and statistically significant coefficients. Moreover, regions belonging to the moderately open economy cluster experience a significant positive premium in employment growth. A positive effect also emerges for the slightly open and fully open clusters when the openness variable is considered in isolation. Regarding institutional quality, cluster 3 shows a negative relationship with convergence, while the decentralization control is not statistically significant. While the β convergence coefficient remains negative and statistically significant, confirming convergence, the ERDF coefficient becomes statistically insignificant and close to zero.

The gender employment gap presents a different narrative. Indeed, for this indicator the catch-up mechanism appears entirely disconnected from regional institutional frameworks, as not a single institutional, political, or administrative cluster is statistically significant. Only when considered in isolation, decentralization displays a positive effect in moderately decentralized systems. The ERDF coefficient is statistically insignificant, and the β coefficient remains negative and statistically significant.

Finally, for sectoral employment structure, among the four control variables, only the political orientation of national governments is statistically significant, with negative coefficients relative to the baseline of a right government. Institutional quality, by contrast, becomes significant only when considered in isolation, with higher levels of quality displaying a positive effect. Both the β coefficient and the ERDF variable are statistically insignificant.

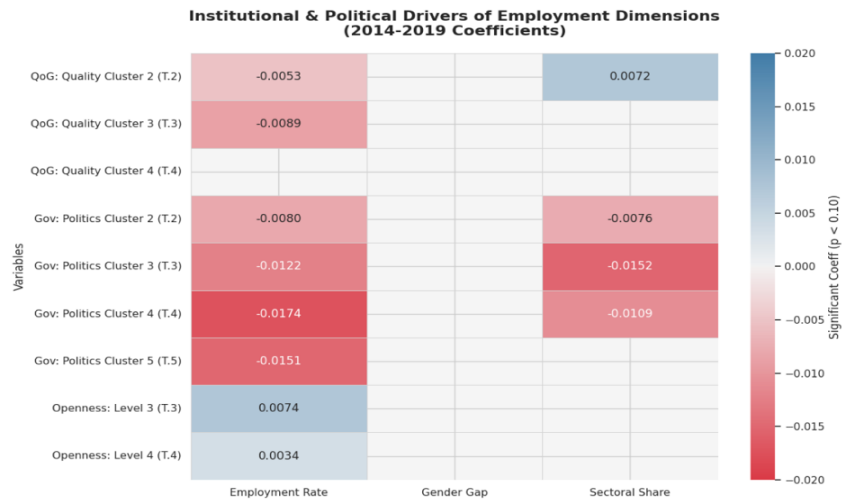


FIGURE 15: Heatmap of statistically significant controls regression coefficients from the conditional β -convergence models for the three employment dimension indicators.. Source: figure created by the author.

CHAPTER 4: DISCUSSION & LIMITATIONS

This chapter interprets the findings detailed in the previous section to answer the research question formulated in Chapter 2. Indeed the objective of the thesis was threefold: analyse if NUTS 2 regions are experiencing convergence, evaluate the relationship between ERDF funds and regional convergence in the economic, social and labour market dimension, and identify if political, institutional or spatial variables influence the observed heterogeneity of outcomes. The results show that, although convergence is taking place across all three dimensions, albeit with varying intensity, this process is only weakly associated, and in some cases not associated at all, with the direct effect of the funds. Instead, the results suggest that convergence is more significantly driven by spatial spillovers and regional institutional conditions. This section will unpack these findings and provide evidence-based policy recommendations, challenging the one-size-fits-all assumption of Cohesion Policy.

H1: The convergence hypothesis

The first hypothesis expected that a positive convergence would occur across all the three dimensions over the 2014-2020 programming period. The empirical results provide a nuanced support for this first hypothesis. Indeed, while the β convergence models show a reduction of overall regional disparities across NUTS 2 regions, the analysis reveals that convergence is multi-speed across indicators and across territories.

Specifically, the findings confirm a catch-up process regarding GDP per capita measured in PPS and labour productivity, with the former aligning with the so-called "iron law of convergence" identified by Barro and Sala-i-Martin (1992) who suggest that economies historically converge at a rate of 1–2% per year without any policy intervention. From a theoretical perspective, the convergence process seems to suggest a structural automatic mechanism due to diminishing returns to capital, broadly consistent with neoclassical convergence theory (Solow and Swan, 1956). However, the higher speed of convergence in labor productivity indicates that efficiency gains are spreading across the Union faster than overall wealth, aligning with endogenous growth theories where the diffusion of best practices and knowledge allows lagging regions to optimize existing structures. This trend does not apply to the technological dimension.

In fact, a critical point of the analysis arises when assessing that convergence for the technological dimension is slower than the other parameters of the economic dimension. This finding confirms the concerns presented by Caravella et al (2023), who highlight the necessity of three main key factors to shape EU regions' dynamics: the concentration of large and high-tech and knowledge intensive businesses, the presence of a qualified workforce and a sustained aggregate demand. However, these elements are unevenly distributed across European regions and thus convergence is not automatic. As noted by Bolter et al. (2020), the capacity of a region to absorb knowledge is a fundamental condition for structural change. This suggests that convergence follows a path dependent process, aligning with Endogenous Growth Theory and New Economic Geography (Hervas-Oliver et al. 2021). These theories emphasize that technological capabilities depend on human capital and innovation ecosystems, which tend to remain geographically concentrated, justifying the need for a policy intervention (Barca et al., 2012). This means that even though a region may display a catch-up process in its general economic growth, it does not necessarily translate into a structural transformation of the economy, which is shaped by long-term specialization patterns. Consequently, the analysis indicates that, during the 2014-2020 period, NUTS 2 regions have experienced an income catch-up without effectively bridging the structural-technological gap.

Evidence of convergence is also present across the social dimension, confirming an extension of convergence outside the economic dimension. Indeed, while the findings for life expectancy and the level of attainment of tertiary education reflects a slow and gradual

harmonization of healthcare standards, living conditions, and social welfare, the social domain exhibits a lower speed of convergence compared to the economic one. Moreover, the absence of convergence in the sectoral employment structure, while the general employment level and the gender employment gap both exhibit clear convergence, confirms the insights from the technological development convergence. Indeed, the structural composition of regional labour markets is not becoming more homogeneous across NUTS 2 regions, confirming that structural transformation and long-term employment creation is a path dependent and not automatic process. The finding that the NEET rate exhibits a higher speed of convergence compared to the other social indicators, must be interpreted in light of these results. Indeed, if the NEET rate is falling, but the economy is not undergoing a structural change, there is a risk that youth are being reintegrated into low-skill, precarious, or traditional service-sector jobs, meaning that this finding represents a quantitative success rather than a qualitative one (European Commission, 2018/2020).

The effect of the COVID-19 pandemic does not seem to have had a major impact on the convergence process. Economic indicators remained stable, likely saved by the EU tools to mitigate the effects of the shock, namely REACT-EU and CARE (Costache & Bolos). Differently from the economic dimension, social convergence and gender labour market dynamics appears more fragile and sensitive to the external shock of COVID19. For instance, the 17% decrease in the coefficient of the gender gap indicator confirms the “she-cessions” thesis (Bluedorn, J., et al, 2021) as the number of women employed decreased by 1.5 million across the EU (EIGE). Some studies have shown that women are more likely to work in social sectors particularly hit by the COVID-19 crisis, such as the retail, accommodation, residential care activities, activities of households as employers of domestic personnel and apparel manufacturing sectors (Mongey et al. 2020) and that the challenges related to unpaid care work and work–life balance further exacerbate the inequalities.

The key substantive lesson is that the convergence in Europe during 2014–2020 is dependent on the indicator under analysis and there are persistent structural divides. Generally, convergence is stronger for general economic and labour-market outcomes, weaker for technological and structural variables, and more fragile in the social domain. This justifies the need for policy support and not just market-driven adjustment mechanisms in order to shape long-term cohesion outcomes.

H2: the multidimensional and fund-driven convergence hypothesis

While H1 analyzed the presence of convergence across the different indicators, H2 aims to determine if ERDF-funded allocations over the period 2014-2020 can be considered a driver of this process. The results suggest that the catch-up process appears independent of the funds for most of the indicators, challenging the one-size-fits-all assumption that Cohesion Policy’s transfers mechanically drive regional convergence.

In the economic dimension, the findings for GDP per capita (PPS) and technological development, although limited, suggest that the detected catch-up process is mainly driven by endogenous mechanisms, consistently with neoclassical growth theory, according to which poorer regions tend to grow faster regardless of policy intervention. Most notably, the negative relationship between ERDF funding intensity and labour productivity is related to two plausible interpretations. Firstly, the ERDF is systematically allocated to regions with lower administrative and productive capacity which fall into the “Regional Development Trap”. The latter refers to the long-term regional economic stagnation occurring at varying levels of development and characterized by a stable state of low development and low growth (Diemer, A., et al, 2022). Falling into this type of bad equilibrium is usually associated with self-reinforcing mechanisms linked to institutional failures or stagnating productivity (Hsieh and Klenow 2010) and it suggests that simply pouring money into lagging regions does not automatically translate into productivity gains. Secondly, the composition of ERDF spending

during the 2014–2020 period is heavily weighted towards hard infrastructure, transport, and physical capital, generating short-term GDP effects without upgrading the technological and organisational efficiency that drives productivity (European Commission, 2022).

These findings are further reinforced by the evidence of lack of structural economic change. Indeed, while the employment rate itself shows a modest but significant positive association with ERDF intensity, this convergence pattern is neither gender-neutral nor does it translate into broader sectoral structural change. More specifically, the funds appear to have a negative effect on the reduction of the gender employment gap. A plausible explanation could lie in the sectoral composition of ERDF spending: according to the ex-post evaluation of the European Commission ERDF allocations during 2014–2020 were heavily concentrated in construction, transport infrastructure, and industrial modernisation, sectors with a structurally male-dominated workforce.

Furthermore, the lack of impact on education confirms that, while the ERDF can stimulate short-term job creation, it is not the primary driver of human capital formation, which remains the domain of the European Social Fund (ESF). A different pattern emerges for the NEET indicator where the funds show a positive association with facilitating youth integration into education, training, or employment. Nevertheless, this relationship remains indirect and mediated by broader labour-market dynamics, rather than reflecting a direct policy channel specifically targeting youth inclusion.

This finding directly challenges the claimed complementarity between the ERDF's economic and social objectives as set out in the eleven thematic objectives of the 2014–2020 regulation, suggesting that cohesion policy's instruments are not equally suited to addressing all dimensions of regional disparities.

H3: the structural capacity hypothesis

The H3 findings provide support for the claim that convergence and the effectiveness of the ERDF funding depend on four contextual factors, namely the colour of the government, the level of decentralization of competences to the regions, the level of openness of the economy and the quality of the institutions. However, the specific mechanisms diverge from the hypothesis' claim and they diverge across economic, social and employment dimensions.

Firstly, institutional quality seems to have an impact on the effectiveness of the funds in the economic dimension, except for technological development, with regions characterized by intermediate levels of institutional quality, where there is room to catch-up, displaying the strongest convergence dynamics. This pattern suggests that convergence is conditional on institutional capacity, meaning that institutional weaknesses can neutralize the catch-up effects of Cohesion Policy. In the social dimension, the NEET rate reduction is heavily influenced by the quality of regional institutions as regions characterized by weaker governance structures tend to display much poorer performance, suggesting that effective institutions are necessary to translate the convergence opportunities displayed in the previous paragraph into improved social outcomes. Finally, in the employment dimension, the influence of institutional quality is generally more limited as the lack of a systematic relationship between institutional quality and employment indicators suggests that labour-market outcomes are less sensitive to regional administrative capacity and more shaped by broader economic and policy environments.

Moreover, the funding reveals that the political orientation of the national government further influences the ERDF funds' performance on convergence. While balanced and moderate-left configurations tend to display stronger convergence dynamics in the economic dimensions, a distinct pattern emerges for technological development, where both left-polarized and moderately right governments generally favour economic catch-up. This finding aligns with Mazzucato's theory (2014) on the role of the state on technological innovation. Indeed, a leftist state-centric government can lead to a state intervention in high-externalities

technological sectors, catalyzing private investments, and to public investments in research, reinforcing the knowledge-based necessary for technological development. Conversely, right-wing governments tend to favour deregulation (Potrafke, 2010), which can reduce the barriers to technological competition (Conway and Nicoletti, 2006) and carry on pro-market or activation-oriented policies that may facilitate labour-market integration, and convergence in the structural configuration of the labour market. However, while these political orientations are associated with labour market integration, they show a notable lack of ERDF effectiveness. This suggests that EU structural funds do not mechanically generate jobs through funds, but they are driven by local labor market policies. This does not hold for the gender employment gap, which remains insensitive to political ideology, suggesting that female labor market integration is instead driven by deep-rooted, macro-sociological shifts and national-level welfare policies. Similarly, in the social dimension, regions characterized by right political configurations display weaker performance in reducing youth exclusion, suggesting that political priorities affect the design and implementation of inclusion policies. This result indicates that convergence in social outcomes depends not only on economic growth but also on policy choices related to welfare provision, labour-market activation, and education systems. At the same time, political orientation does not systematically affect all social indicators, highlighting that some aspects of social convergence are driven more by structural and demographic factors than by regional political context.

Economic openness emerges as another relevant factor facilitating regional convergence, yet its effect is not universal. The economic and labour market indicators of regions characterized by higher levels of integration into the European market tend to benefit from knowledge spillovers, increased competition, and access to larger demand (Rodríguez-Pose and Crescenzi 2008). However, the findings in the social and sectoral employment dimension display a weaker and less consistent relationship, suggesting that the convergence depends more strongly on institutional capacity and welfare systems than on external economic integration.

Finally, the limited role played by the degree of decentralization of competences implies that the functional capacity and the political orientation of a government have a greater impact than its structural autonomy.

H4: the spatial spillover/concentration hypothesis

The results from the Spatial Durbin Models (SDM) confirm the H4 by showing that spatial spillovers emerge as a central mechanism of European regional convergence dynamics. Across nearly all indicators, the indirect impacts of ERDF funds, namely the effects flowing from neighbouring territories, are stronger than the direct impact. This finding suggests that the performance of a region strongly depends on the performance of its spatial environment. The only exception is the gender employment gap indicator, where the lack of spatial diffusion reinforces the conclusion that gender equality is anchored in national institutional frameworks rather than regional proximity. Complementing these results, the gap analysis reveals that persistent structural lagging regions across more indicators are geographically clustered, most notably in Italy's Mezzogiorno, Eastern Germany and Europe, and France's outside territories. These findings validate the persistent core-periphery structures described by the New Economic Geography theory.

In the economic dimension, the geography of lagging regions points to a persistent divide. This spatial concentration in Southern European peripheral regions, in some French overseas territories, and in some parts of Eastern Germany, suggests that economic divergence reflects a process of cumulative causation (Kaldor, 1989). As industries gravitate towards high demand, they increase regional differences by leaving lagging regions in a stable state of low growth. Indeed, the economic performance of a region depends not only on its own infrastructure and productive base, but also on the characteristics of neighbouring regions and

the spatial environment in which it is embedded (Laird et al. 2005, Pereira and Roca-Sagalés 2003). This spatial pattern is also visible in Figure 16.

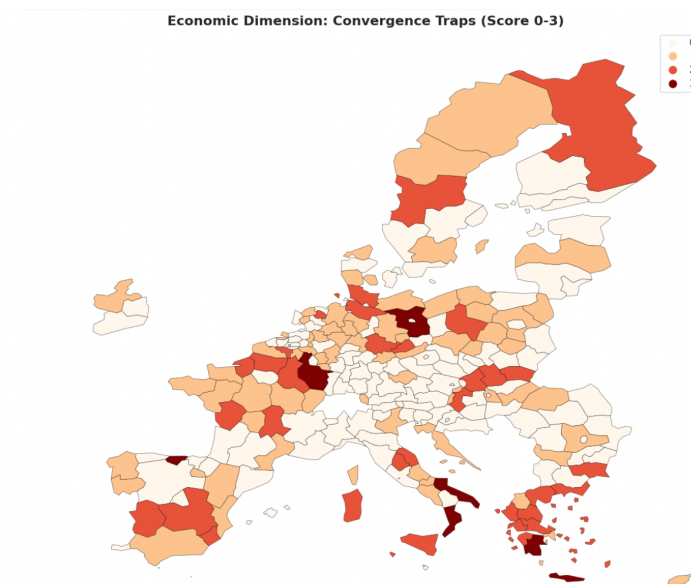


FIGURE 16: Choropleth map of EU NUTS 2 regions displaying the economic convergence trap score (0–3)
Source: figure created by the author.

The social dimension reveals a different geographical story. Indeed, the most severely lagging regions are concentrated in Eastern Europe and Germany, with less pronounced cases also in Southern Italy. The club analysis highlights that social disadvantage has its own territorial logic and may persist even where some degree of economic adjustment is taking place, hinting at the need for a specific a specific set of social structural reforms. This spatial pattern is also visible in Figure 17.

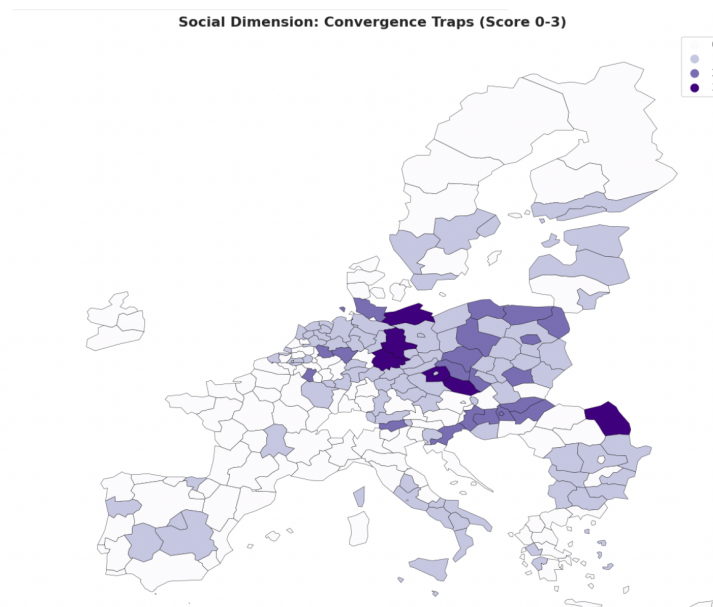


FIGURE 17. Choropleth map of EU NUTS 2 regions displaying the social convergence trap score (0–3). Source: figure created by the author.

Finally, in the employment dimension, clusters of non-converging regions emerge in French peripheral territories, Belgian provinces, parts of Eastern Germany, and selected peripheral regions in Southern and Northern Europe. This pattern suggests that labour-market divergence

is deeply rooted in long-term characteristics, such as skills development and polarization of unemployment rates, driven by geographically clustered changes in relative labour demand (Puga, 2002). This spatial pattern is also visible in Figure 18.

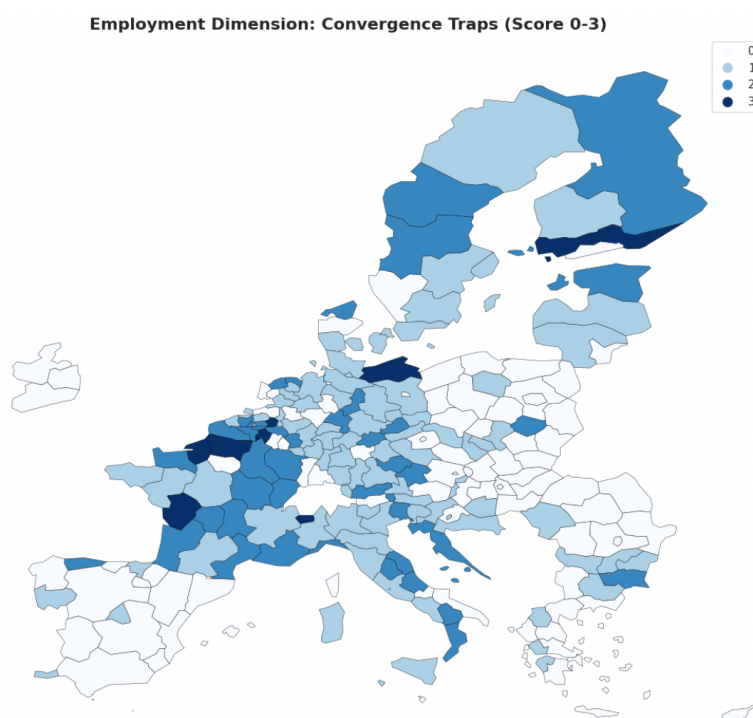


FIGURE 18: Choropleth map of EU NUTS 2 regions displaying the employment convergence trap score (0–3)
Source: figure created by the author.

These overall findings support the prediction of New Economic Geography theory that convergence is a spatial phenomenon and integration can generate self-reinforcing core–periphery structures. The identification of structurally trapped social and employment regions that overlap only partially with economically trapped regions is a key finding: the problem of "left-behind places" is multi-dimensional and cannot be addressed by a single instrument designed primarily for economic ends.

Hypothesis	Expected result	Actual result	Verdict
H1: Convergence hypothesis	Positive convergence across all three dimensions over the 2014–2020 period.	Multi-speed convergence: strong in the economic dimension, weaker in the social dimension, absent for sectoral employment structure and technology.	Partially confirmed. Confirmed for GDP and employment; not for technology and social dimensions.
H2: Fund-driven convergence hypothesis	ERDF primarily drives economic convergence, which in turn improves social and labour market outcomes (hierarchical effect).	ERDF non-significant for most indicators; negative for labour productivity; widens gender employment gap; no significant impact on social sector.	Rejected. Convergence driven by endogenous mechanisms, not by ERDF transfers.
H3: Structural Capacity hypothesis	ERDF more effective in regions with higher decentralization, political stability, and left-wing government (positive conditionality).	Institutional quality and economic openness matter; balanced/left-leaning governments favour GDP convergence; decentralization has limited or negative effect.	Partially confirmed. Confirmed for institutional quality and openness; political orientation more nuanced than expected; decentralization not confirmed.
H4: Spatial Spillover hypothesis	Neighbouring regions' growth positively affects a region's convergence (positive spatial effect).	Confirmed across nearly all indicators; indirect effects exceed direct effects. Exception: gender employment gap shows no spatial diffusion. Core-periphery clusters detected.	Confirmed. SDM validates strong spatial dependence; gender gap is the only exception.

TABLE 12: Summary of expected versus actual results for each of the four research hypotheses. Source: table created by the author.

4.1 Limitations

Despite this study's presented strengths, several limitations must be acknowledged, particularly in relation to data quality, methodological choices, and the broader generalizability of findings.

The first concerns the possible multidimensionality and overlap of the selected indicators. Indeed, even though they are grounded in the academic literature and in the objectives of Cohesion Policy, the three domains under analysis are not mutually independent. For instance, the gender employment gap may serve as both a labour market and a social indicator, as well as labour productivity, which captures economic efficiency and employment dynamics. As a result, the distinction between economic, social, and employment dimensions should not be interpreted as a rigid separation between fully independent domains. Moreover, data availability necessitates the use of proxy variables for some concepts. For instance, in the absence of data on technological patents as they are not disclosed to the public, employment in high-tech sectors was utilized as a proxy for regional innovation capacity. Similarly, life expectancy was employed as the indicator for quality of life, hospitals quality and healthcare standards.

Secondly, the analysis encountered challenges related to data gaps and NUTS 2 nomenclature inconsistencies. The dataset-cleaning process is outlined in Chapter 2. Although this procedure was conducted as consistently as possible using official correspondence tables and transparent cleaning rules, some degree of measurement error and loss of territorial precision is inevitable. A further limitation regarding data derives from the scalar mismatch between regional convergence data and institutional control variables. Indeed, the latter are measured at the national rather than regional level due to data availability. Therefore, the effects detected should be interpreted as identifying broad contextual effects rather than fully region-specific governance mechanisms.

From a methodological perspective, it is worth noting that ERDF intensity is modelled as a conditioning factor of convergence, but the allocation of funds is not random and is itself targeted toward structurally weaker regions. This means that regions receiving more funding are often those facing structural constraints, making it difficult to isolate the independent effect of funding from the underlying disadvantages that justified the allocation in the first place. This creates potential endogeneity and makes causal attribution more difficult; therefore the empirical strategy should be identified as showing statistical associations rather than fully causal effects.

CHAPTER 5: CONCLUSION AND POLICY RECOMMENDATIONS

By employing a multidimensional quantitative analytical framework, the results challenge the one-size-fits-all approach of Cohesion Policy, which assumes a mechanical and automatic convergence as a consequence of financial transfers.

The empirical findings indicate a spatially asymmetrical and multi-speed convergence across NUTS 2 regions for the 2014-2020 MFF programming period. While generally for economic indicators a catch-up process is observed, the convergence is more limited for the social dimension and the structural dimension of the labour market. These divergences, coupled with a stagnation of technological development, suggest that economic catch-up is not associated with a structural transformation of the economy and of public welfare. Furthermore, the empirical models demonstrate that the observed convergence is primarily driven by endogenous structural mechanisms rather than by the direct impact of ERDF financial transfers. In fact, the negative relationship between the money allocations and labour productivity convergence suggests that funds are often trapped in inefficient local systems suffering from poor absorption capacity and have little to no impact on the social sector. The results also confirmed that the convergence is dependent on pre-existing regional characteristics, such as institutional quality, openness of the economy and government ideology, as well as on the spatial effects of neighbouring regions. Indeed, the convergence club analysis reveals that non-developing regions are tightly clustered geographically; however, the thesis showed that the clusters vary according to the dimension under analysis, meaning that an intervention limited to the economic dimension is not sufficient to achieve the broader objectives of cohesion policy.

These findings reveal severe inefficiencies in the current Cohesion Policy framework. First of all, the EU cannot assume that the simple allocation is sufficient to drive regional catch-up and that a one-size-fits-all approach should therefore be abandoned. Moreover, evaluating ERDF success purely on economic outputs, such as GDP, masks failures in the social and labour market dimensions, including the widening gender employment gap and the persistence of rigid structure of the economy's sectors. Ultimately, directing financial resources into isolated lagging regions without considering the spatial environment will fail to trigger structural transformation. According to the results outlined above, this thesis proposes different policy recommendations.

Each recommendation follows a precise structure: it starts from the identification of a problem, moving toward the proposed mechanism to address it as well as institutional constraint of implementation, concluding with a clear operationalization framework. These proposals are mainly addressed to inform legislative bodies, specifically DG Regio and EP REGI Committee in order to target their open consultations for post-2027 MFF. Moreover, they serve as a strategic contribution to the work of research and academic institutions, including ESPON, CEPS, Bruegel and think tanks of regional studies.

1. Integrate the cohesion policy in the green and digital transition

The architectural separation of the EU objectives creates a systemic inefficiency as investments in one domain generate positive externalities for the other that go uncaptured in programming logic, monitoring frameworks, and ex-post evaluation. Moreover lagging regions face a compounded disadvantage as they lack digital infrastructure and the human capital required for high-value green technologies yet are asked to address these in separate operational programmes. Indeed, currently, IT skills, R&D resources and personnel vary widely from region to region, hindering further economic and social development for some regions and labour and skills shortages have become a major challenge in a variety of occupations and sectors. Furthermore, the transition away from fossil fuels risks asymmetrically impacting the

social and employment dimensions of certain regions dependent on it, leading to significant job losses and localized social discontent.

In order to ensure equitable regional development, the advancements in the green and digital transitions must account for the significant disparities between regions that undergo these transformations. Three instruments are proposed. Firstly, ERDF operational programmes should be required to dedicate a minimum threshold to formally certified "twin transition" projects, defined as investments that simultaneously advance both digital and green objectives, with measurable targets in both domains. Secondly, Regional Skills Hubs should be introduced as institutional intermediaries to actively leverage the power of knowledge spillovers. Their mandate should consist in co-design curricula for emerging green-digital occupations (European Commission 2023). By intentionally connecting innovation leaders with lagging regions, the EU can facilitate the diffusion of green technologies and digital know-how, ensuring that isolated technological advancements translate into pan-European structural growth. Finally, a share of the Innovation Fund, the EU-level fund already fed by ETS revenues, should be explicitly earmarked for just transition support in fossil-fuel-dependent regions in order to mitigate the adjustment costs of the transitions.

However, the creation of Regional Skills Hubs may lead to a risk of duplication and therefore a fragmentation of the legislative system (European Commission, 2026). Therefore governance clarity is necessary. Furthermore, the direct earmarking of EU ETS revenues faces a binding institutional constraint as Article 10(2) of Directive 2003/87/EC states that revenues flow directly to member states, not to the EU budget. Thus, in the long run, a revision of the ETS directive is proposed. In particular, mandatory expenditure obligation should be introduced in order for the Member States to allocate a fixed percentage toward green and digital goals and the performance monitoring should use a dual scorecard tracking both CO2 reduction metrics and digital adoption rates

2. Reinforce the place-based dimension of cohesion: a four-quadrant classification

The EU classification system categorizes the regions in three groups, namely "less developed" (GDP per head of less than 75% of the EU average), "transition" (GDP per head of more than 75% and less than 90% of the EU average), and the "more developed" regions. This systematically conceals intra-category heterogeneity. Indeed, the club analysis in this thesis has revealed that regions with similar initial income levels can follow radically divergent growth trajectories. For instance, regions starting from a level below the EU average, can be divided between those in a state of active catch-up (poor converging) and those suffering from structural stagnation (poor non-converging). Applying identical instruments and allocation logic to these two fundamentally different regional conditions wastes resources and misdiagnoses the policy problem. Therefore, this thesis argues for a place-based and people-oriented approach.

The mechanism proposed is a four-quadrant matrix typology, similar to the classification presented in Chapter 3, based on two observable variables at the start of each programming cycle: the initial level of development relative to the EU average, and the growth rate relative to the EU average in the previous programming period. According to these conditions, regions would be classified in four groups, namely (i) Pulling ahead, meaning regions with high income and high growth which would receive a minimal cohesion support; (ii) stagnating developed with high income and low growth which would be subject to targeted structural reform and innovation support to avoid falling in a development trap; (iii) active catch-up with low income and high growth which would receive investment-heavy allocations in order to allow for structural convergence rather than mere income; and finally (iv) structural lagging with low income and low growth which would receive a high proportion of technical assistance, accompanied by institutional capacity-building through conditional transfers.

Cohesion Policy would calibrate its instruments and intensity according to the specific conditions that the structurally lagging territory faces. This ensures that regions struggling with specific challenges, such as rural depopulation or border-related bottlenecks, are not overlooked by a uniform system, but are instead supported by policies tailored to their unique path-dependent trajectories. This new system would shift the focus from mere capital injections to deep institutional and structural reforms aimed at unlocking untapped economic potential as a way to achieve growth (Rodríguez-Pose, 2025).

This reclassification may encounter resistance in the Council. Classification should be formalized at the beginning of each MFF programming period using Eurostat NUTS 2 data and a mid-cycle review clause should allow reclassification. The instrument mix for each quadrant should be codified in the Common Provisions Regulation as binding programming guidelines, not merely indicative suggestions. The instrument mix should include each region's unique strengths for development (Morgan 2017), attracting investments aligned with local strengths, embedding firms into global production networks and aligning choices with EU priorities. Moreover, it should also prioritize how the policy is implemented and by whom by investing in people, empowering local actors, ensure transparency and building institutional capacity in the long run.

3. Prioritize cross-border and interregional cooperation

A pivotal finding of the Spatial Durbin Model analysis demonstrated that spatial spillovers exert a great influence on regional convergence dynamics, with the indirect effects of growth and investment from neighbouring territories often having a more significant influence than direct ERDF allocations.

Moreover, the cluster analysis has demonstrated the tendency of structurally lagging regions to geographically concentrate, meaning that purely localized interventions may be fundamentally inadequate if the surrounding regional environment is uniformly depressed. This spatial dimension has often been overlooked in evaluations and in the Cohesion Policy objectives, as for instance INTERREG, the EU's dedicated cross-border cooperation instrument, accounts for only approximately 2.5% of total cohesion funding.

Therefore, to address these spatial imbalances and to prioritize cross-border and interregional integration, three mechanisms are envisaged. Firstly, building on Darvas et al. (2026), regions should be required to allocate a minimum threshold for the inclusion of cross-border projects. Secondly, rules should be reformed to allow dynamic core regions to receive finances specifically for projects that transfer technology, knowledge, or administrative capacity to adjacent lagging regions even if they would not qualify for structural funds. Finally, existing EU macro-regional strategies should be formally integrated into ERDF programming as it would allow for greater coherence and complementarity between policies as well as increased policy effectiveness and impact (European Committee of the Regions, 2022).

However, the "backwash effect" is a fundamental risk as it allows for rural-to-urban flows of capital and skilled labour since the market is bigger. These remote regions will need to devise economic-development programs that emphasize competitive advantages specific to their economies should be developed through these funds and retention incentives should be included (Faridi, 2019). As regarding evaluation, absorption of cross-border funds should be tracked separately from localized ERDF allocations in Commission annual reports.

4. Moving Beyond GDP: a multidimensional evaluation of Cohesion Policy

The analysis provided an empirical refutation of the assumption that economic convergence triggers a catch-up process across the social and labour market dynamics. Indeed, the gap

analysis clearly shows that the geographical distribution of structural lagging regions is not uniform. This misalignment demonstrates that regional development is a fragmented process with dimension-specific bottlenecks. Yet GDP per capita remains the most commonly employed metrics for both regional classification and ERDF performance evaluation. This thesis holds that, to fully capture the social and employment objectives of the ERDF funds, EU policy evaluators must formally integrate a multidimensional measurement framework.

It does so by proposing a formal Cohesion Performance Index (CPI) incorporating three equally weighted composite dimensions, mainly economic, social and labour market in line with article 174 TFEU, as well as an institutional dimension. This CPI would be used in ERDF ex-post evaluations to allow for standardized and multiframework evaluations.

However, weighting choices encode normative priorities and regions would be classified differently according to the indicators chosen. Therefore the solution lies in transparency and methodological openness. Building on the special report of the European Court of Auditors, the European Commission should prepare the ground for an effective review by publishing the full weighting methodology and conducting a sensitivity analysis (European Court of Auditors, 2021). Secondly, in order to operationalize this recommendation, available and reliable data are necessary. As highlighted by the report on Policy Recommendations of ESPON, bottom-up databases which are accessible to policymakers and decision-makers, alongside national, regional, and local authorities should be developed.

5. Managing citizens' expectations: building democratic accountability into cohesion policy delivery

Structural funds produce effects contingent on institutional quality, administrative capacity, and political stability. A persistent gap between citizens' expectations and the actual functioning of ERDF creates political disillusionment and provides fertile ground for Eurosceptic narratives and the spread of populist parties. For the local population and civil society within NUTS 2 regions, the findings of this research serve as a critical tool for managing expectations regarding European financial assistance. Indeed, the results demonstrate that the ERDF funds do not function as an automatic or rapid convergence instrument. Rather, structural funds are instruments for long-term structural and infrastructural growth, and they should not substitute a national welfare system or an active local labor market policy. On the contrary, one of the main takeaways from the analysis is that administrative capacity and political stability of national and regional governments is pivotal for the effectiveness of the funds. Consequently, this thesis holds that citizens and local stakeholders must pressure their regional authorities to prioritize institutional quality, transparency, and the efficient absorption of funds.

A Cohesion Transparency Dashboards on the model of the Open Data Platform is proposed. There, ERDF operational programme must maintain a publicly accessible, real-time tracking platform showing fund allocation, project status, disbursement rates, and outcome indicators at the individual project level. The development of e-Cohesion systems would therefore be beneficial both for programme authorities, as a digitalized platform has been found to reduce the administrative burden in simplifying the implementation of the programmes and the interoperability between e-Cohesion systems and national databases and systems, and for the citizens (European Commission, 2023). The EU Commission has already launched the platform Kohesion, which aggregate project data and the Common Provisions Regulation 2021/1060 imposes to Member states to publish. However, a standardization of a platform is envisageable. Building on Boyd (2018), this thesis proposes a framework for a cohesive Application programming interfaces (API) adoption in Cohesion policy. This inclusion would allow for the alignment of API adoption with policy goals, the creation of platforms and ecosystem based on

APIs, an organization of teams and development of an API culture, and the design of processes based on API best practices (Boyd et al, 2020).

This proposal is politically sensible and DG REGIO should develop a standardized open-data API for ERDF project reporting, accompanied by an ex.post evaluation of the European Court of Auditors.

BIBLIOGRAPHY

- #CohesionAlliance (2024), *A renewed Cohesion Policy post-2027 that leaves no one behind*. European Committee of the Regions. Available at: <https://cor.europa.eu/sites/default/files/2024-07/renewed-cohesion-policy-post-2027-en.pdf>
- Abrahám, J. and Vosta, M. (2020), *Impact of the COVID-19 Pandemic on EU Convergence*. European Research Studies Journal. Available at: <https://www.mdpi.com/1911-8074/15/9/384>
- Armingeon, K., Engler, S., Leemann, L. and Weisstanner, D. (2025), Comparative Political Data Set. Institute of Political Science, University of Bern. Available at: <https://cps-data.org/>
- Armstrong, H.W. and Taylor, J. (2000), *Regional Economics and Policy*. Blackwell Publishers. Available at: <https://www.e-elgar.com/shop/gbp/the-economics-of-regional-policy-9781840640083.html>
- Arnaoutoglou, P. (2022), *Institutions and Cohesion Policy in the European Union*. MPRA Paper 113543, University Library of Munich. Available at: <https://ideas.repec.org/p/pramprapa/113543.html>
- Arthur, W.B. (1990), Positive Feedbacks in the Economy. *Scientific American*. Available at: <https://doi.org/10.1038/scientificamerican0290-92>
- Bachtler, J. et al. (2013), *EU Cohesion Policy and European Integration: The Dynamics of EU Budget and Regional Policy Reform*. Ashgate Publishing. Available at: https://www.researchgate.net/publication/287939909_EU_Cohesion_policy_and_European_integration_The_dynamics_of_EU_budget_and_regional_policy_reform
- Baldwin, R. and Wyplosz, C. (2013), *The Economics of European Integration*. McGraw-Hill Education. Available at: <https://it.scribd.com/document/436860470/The-Economics-of-European-Integration>
- Barca, F. (2009), *An Agenda for a Reformed Cohesion Policy: A place-based approach to meeting European Union challenges and expectations*. European Commission. Available at: https://www.europarl.europa.eu/meetdocs/2009_2014/documents/regi/dv/barca_report/_barca_report_en.pdf
- Barca, F., McCann, P. and Rodríguez-Pose, A. (2012), The case for regional development intervention: Place-based versus place-neutral approaches. *Journal of Regional Science*. Available at: <https://doi.org/10.1111/j.1467-9787.2011.00756.x>
- Barrios, S. and Strobl, E. (2009), The dynamics of regional inequalities. *European Economic Review*. Available at: <https://ideas.repec.org/a/eee/regeco/v39y2009i5p575-591.html>
- Barro, R.J. and Sala-i-Martin, X. (1992), Convergence. *Journal of Political Economy*. Available at: <https://doi.org/10.1086/261816>
- Becker, S.O. et al. (2018), Effects of EU Regional Policy: 1989-2013. *Regional Science and Urban Economics*. Available at: <https://doi.org/10.1016/j.regsciurbeco.2017.12.001>
- Begg, I. (2010), Cohesion or Confusion: A Policy Searching for Objectives. *Journal of European Integration*. Available at: <https://www.tandfonline.com/doi/abs/10.1080/07036330903375115>

- Bisello, M. and Mascherini, M. (2017), The Gender Employment Gap: Costs and Policy Responses. Intereconomics. Available at: <https://www.intereconomics.eu/contents/year/2017/number/1/article/the-gender-employment-gap-costs-and-policy-responses.html>
- Bluedorn, J. et al. (2021), Gender and Employment in the COVID-19 Recession: Evidence on "She-cessions". International Monetary Fund. Available at: <https://www.imf.org/-/media/Files/Publications/WP/2021/English/wpiea2021095-print-pdf.ashx>
- Boldrin, M. and Canova, F. (2000), Inequality and convergence in Europe's regions: reconsidering European regional policies. Economic Policy. Available at: https://www.researchgate.net/publication/227542753_Inequality_and_convergence_in_Europe's_regions_reconsidering_European_regional_policies
- Bolter, K. and Robey, J. (2020), Agglomeration Economies: A Literature Review. W.E. Upjohn Institute for Employment Research. Available at: <https://research.upjohn.org/cgi/viewcontent.cgi?article=1256&context=reports>
- Bourdin, S. (2019), Does the Cohesion Policy reduce regional disparities? Support for the spatial externalities hypothesis. Journal of European Integration. Available at: https://www.researchgate.net/publication/327652520_Does_the_Cohesion_Policy_Have_the_Same_Influence_on_Growth_Everywhere_A_GWR_Approach_in_Central_and_Eastern_Europe
- Bourdin, S. et al. (2021), Towards a territorialisation of the circular economy: The proximity of stakeholders and resources matters. Cambridge Journal of Regions Economy and Society. Available at: https://www.researchgate.net/publication/377974233_Towards_a_territorialisation_of_the_circular_economy_The_proximity_of_stakeholders_and_resources_matters
- Boyd, M., Vaccari, L., Posada, M. and Gattwinkel, D. (2020) An Application Programming Interface (API) framework for digital government. Luxembourg: Publications Office of the European Union. doi: 10.2760/515647. Available at: <https://share.google/5RnPIvcxhsYE9EyHR>
- Breidenbach, P., Mitze, T. and Schmidt, C.M. (2016), EU Structural Funds and Regional Income Convergence – A sobering experience. Available as SSRN paper. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2758674
- Brunazzo, M. (2016), The History and Evolution of EU Cohesion Policy. In: S. Piattoni and L. Polverari, eds., EU Cohesion Policy after Enlargement. Palgrave Macmillan. Available at: https://www.researchgate.net/publication/315897669_The_history_and_evolution_of_Cohesion_policy
- Bruno, G.S.F. et al. (2014), The Rise of NEET and Youth Unemployment in EU Regions after the Crisis. Comparative Economic Studies. Available at: <https://doi.org/10.1057/ces.2014.27>
- Bucur Vasile and Iulia Andreea (2012), National and Regional Coordinates of the Real Convergence Process Intensity in the Enlarged European Union. Centre for European Studies. Available at: https://www.researchgate.net/publication/233731315_National_and_Regional_Coordinates_of_the_Real_Convergence_Process_Intensity_in_the_Enlarged_European_Union

- Burda, M. and Wyplosz, C. (2008), *Macroeconomics: A European Text*. Oxford University Press. Available at: https://www.researchgate.net/publication/227467729_Macroeconomics_A_European_Text
- Burian, T. and Brčák, J. (2014), *Convergence Process in the European Region - Cluster Analysis*. Research Note. Available at: <https://link.springer.com/article/10.1007/s11294-014-9488-6>
- Butkus, M. et al. (2018), What Is the Evolution of Convergence in the EU? Decomposing EU Disparities up to NUTS 3 Level. Research Institute, Siauliai University. Available at: <https://www.mdpi.com/2071-1050/10/5/1552>
- Butkus, M. et al. (2018), What Is the Evolution of Convergence in the EU? Decomposing EU Disparities up to NUTS 3 Level. *Sustainability*, 10(5), p. 1552. Available at: <https://doi.org/10.3390/su10051552>
- Caravella, S. et al. (2023), The diffusion of digital skills across EU regions: structural drivers and polarisation dynamics. *Regional Studies, Regional Science*. Available at: <https://doi.org/10.1080/21681376.2023.2265498>
- Castro Vieira, R. (2021), The COVID-19 Pandemic and the EU's Response. *European Papers*. Available at: https://www.researchgate.net/publication/355111981_The_European_response_to_the_COVID-19_crisis_at_the_regional_level_and_its_effects_on_the_shaping_of_the_new_Europe_an_Cohesion_Policy
- Cavenaile, L. and Dubois, D. (2011), An empirical analysis of macroeconomic convergence in EU. *Applied Economics Letters*. Available at: <https://doi.org/10.1080/13504851.2011.554366>
- Cerro, E. (2022), 2021-2027 Cohesion policy EU budget allocations. European Association of Development Agencies (EURADA). Available at: <https://www.eurada.org/news/detail/2021-2027-cohesion-policy-eu-budget-allocations>
- Coccia, M. and Benati, I. (2024), Negative effects of high public debt on health systems facing pandemic crisis: Lessons from COVID-19 in Europe to prepare for future emergencies. *AIMS Public Health*. Available at: <https://pmc.ncbi.nlm.nih.gov/articles/PMC11252587/>
- Conway, P. and Nicoletti, G. (2006), Product market regulation in the non-manufacturing sectors of OECD countries: Measurement and highlights. OECD Economics Department Working Papers. Available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2006/12/product-market-regulation-in-the-non-manufacturing-sectors-of-oecd-countries_g17a190e/362886816127.pdf
- Costache, C.M. and Boloş, M.I. (2024), On European Union Economic Growth: Is Cohesion Policy Still Relevant?. *Annals of Faculty of Economics, University of Oradea*. Available at: <https://ideas.repec.org/a/ora/journl/v2y2024i2p115-126.html>
- Crescenzi, R. and Giua, M. (2020), One or many Cohesion Policies of the European Union? On the differential economic impacts of Cohesion Policy across member states. *Regional Studies*. Available at: <https://doi.org/10.1080/00343404.2019.1665174>

- Dall'erba, S. and Le Gallo, J. (2008), Regional convergence and the impact of European structural funds over 1989-1999: A spatial econometric analysis. Papers in Regional Science. Available at: <https://doi.org/10.1111/j.1435-5957.2008.00184.x>
- Darvas, Z. et al. (2026), National plans, regional voices: cohesion policy in the next European Union budget. Bruegel. Available at: <https://www.bruegel.org/policy-brief/national-plans-regional-voices-cohesion-policy-next-european-union-budget>
- Darvas, Z., Martins, A.M., Mazza, J. and Ravillard, P. (2026), The impact of European Union regional policy: a review of the evidence. Bruegel. Available at: https://www.researchgate.net/publication/318285230_The_Impact_of_the_Regional_Policy_on_the_European_Economy
- De Dominicis, L. (2014), Inequality and Growth in European Regions: Towards a Place-based Approach. Spatial Economic Analysis. Available at: <https://www.tandfonline.com/doi/epdf/10.1080/17421772.2014.891157?needAccess=true>
- Di Caro, P. and Fratesi, U. (2021), One policy, different effects: estimating the region-specific impacts of EU cohesion policy. Journal of Regional Science. Available at: <https://re.public.polimi.it/retrieve/e0c31c12-81e3-4599-e053-1705fe0aef77/Di%20Caro%20Fratesi%202022%20JoRS%20One%20policy%2C%20different%20effects%20-%20Estimating%20the%20region-specific%20impacts%20of%20EU%20cohesion%20policy%20%28published%29.pdf>
- Di Cataldo, M. and Monastiriotis, V. (2020), Regional needs, regional targeting and regional growth: an assessment of EU Cohesion Policy in the UK regions. Regional Studies. Available at: <https://doi.org/10.1080/00343404.2018.1498073>
- Diaz del Hoyo, J.L. et al. (2017), Real convergence in the euro area: A long-term perspective. ECB Occasional Paper Series. Available at: <https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op203.en.pdf>
- Diemer, A., Iammarino, S., Rodríguez-Pose, A. and Storper, M. (2022), The Regional Development Trap in Europe. Economic Geography. Available at: <https://doi.org/10.1080/00130095.2022.2080655>
- Ederveen, S., de Groot, H.L.F. and Nahuys, R. (2006), Fertile Soil for Structural Funds? A Panel Data Analysis of the Conditional Effectiveness of European Cohesion Policy. Kyklos. Available at: <https://doi.org/10.1111/j.1467-6435.2006.00318.x>
- EIGE (2021), Gender equality and the socio-economic impact of the COVID-19 pandemic. European Institute for Gender Equality. Available at: https://eige.europa.eu/sites/default/files/documents/20211734_mh0921078enn_pdf.pdf
- Esposti, R. and Busoletti, S. (2008), Impact of Objective 1 funds on regional growth: Convergence club and evaluation in the European Union. Journal of Economic Integration. Available at: <https://ideas.repec.org/a/taf/regstd/v42y2008i2p159-173.html>
- Eurofound (2012), NEETs – Young people not in employment, education or training: Characteristics, costs and policy responses in Europe. Publications Office of the European Union. Available at: <https://doi.org/10.2806/41578>
- European Commission (2005), EQUAL guide on gender mainstreaming. Office for Official Publications of the European Communities. Available at: https://ec.europa.eu/employment_social/equal_consolidated/data/document/gendermain_en.pdf

- European Commission (2010), Investing in Europe's future: Fifth report on economic, social and territorial cohesion. Publications Office of the European Union. Available at: https://ec.europa.eu/regional_policy/en/information/publications/reports/2010/fifth-report-on-economic-social-and-territorial-cohesion-investing-in-europe-s-future
- European Commission (2018), Study on the Youth Guarantee in light of changes in the world of work: Emerging challenges related to young people's transition into the labour market. Publications Office of the European Union. Available at: <https://doi.org/10.2767/508325>
- European Commission (2022), Cohesion in Europe towards 2050: Eighth report on economic, social and territorial cohesion. Publications Office of the European Union. Available at: <https://doi.org/10.2776/624081>
- European Commission (2023), Commission Staff Working Document: Enhancing the usability of the EU Taxonomy and the overall EU sustainable finance framework. SWD(2023) 209 final. Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52023SC0209>
- European Commission (2023), Digitalisation in EU Cohesion Policy: new report highlights how new requirements on digitalisation have reduced red tape. Available at: https://ec.europa.eu/regional_policy/whats-new/newsroom/13-07-2023-digitalisation-in-eu-cohesion-policy-new-report-highlights-how-new-requirements-on-digitalisation-have-reduced-red-tape_en
- European Commission (2023), Communication on Harnessing Talent in Europe's Regions (COM/2023/32 final). European Commission. Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52023DC0032>
- European Commission (2024), Cohesion policy benefits EU's economy and regions. Joint Research Centre. Available at: https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/cohesion-policy-benefits-eus-economy-and-regions-2024-04-11_en
- European Commission (2022), Ex post evaluation of the European Regional Development Fund and Cohesion Fund 2014-2020. Directorate-General for Regional and Urban Policy. Available at: https://ec.europa.eu/regional_policy/policy/evaluations/ec/2014-2020_en
- European Commission (2026), Cohesion Policy: The EU's main investment policy. European Commission. Available at: https://ec.europa.eu/regional_policy/policy/what/investment-policy_en
- European Commission (2026), Glossary: Cohesion policy. European Commission. Available at: https://ec.europa.eu/regional_policy/policy/what/glossary/cohesion-policy_en
- European Commission (2026), Programming and implementation. European Commission. Available at: https://ec.europa.eu/regional_policy/policy/how/programming-and-implementation_en
- European Commission (2026), Commission Staff Working Document: Ex-post Evaluation of the Internal Security Fund - Police (ISF-P) for the 2014-2020 programming period. SWD(2026) 79 final, 3 March. Brussels: European Commission. Available at: [https://ec.europa.eu/transparency/documents-register/api/files/SWD\(2026\)79?ersIds=090166e52a07503f](https://ec.europa.eu/transparency/documents-register/api/files/SWD(2026)79?ersIds=090166e52a07503f)
- European Commission, Directorate-General for Regional and Urban Policy (2024), Ninth report on economic, *social and territorial cohesion*. Publications Office of the European Union. Available at: <https://doi.org/10.2776/264833>

- European Committee of the Regions (2021), The gender dimension of structural and cohesion funds 2021–2027, with a focus on the preparation of the operational programmes. European Committee of the Regions. Available at: <https://cor.europa.eu/en/our-work/opinions/cdr-2503-2021>
- European Committee of the Regions (2021), The impacts of the COVID-19 pandemic on EU cohesion and EU cohesion policy. European Committee of the Regions. Available at: [https://www.europarl.europa.eu/RegData/etudes/ATAG/2022/699618/IPOL_ATA\(2022\)699618_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/ATAG/2022/699618/IPOL_ATA(2022)699618_EN.pdf)
- European Committee of the Regions (2022), Opinion of the European Committee of the Regions — Towards a macro-regional strategy in the Mediterranean, Official Journal of the European Union. Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52022IR2167&qid=1769831743998>
- European Court of Auditors (2021), Performance-based budgeting in the EU budget: progress made but more work needed to show results. Special Report 24/2021. Luxembourg: Publications Office of the European Union. Available at: <https://op.europa.eu/webpub/eca/special-reports/performance-24-2021/en/>
- European Economic Community (1957), Treaty establishing the European Economic Community (Treaty of Rome). Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=LEGISSUM:xy0023>
- European Parliament (2021), Adapting cohesion policy rules to respond to COVID-19. European Parliamentary Research Service. Available at: <https://op.europa.eu/webpub/eca/special-reports/CRII-2-2023/en/>
- European Parliament (2024), The future of EU cohesion: Scenarios and their impacts on regional inequalities. European Parliamentary Research Service. Available at: [https://www.europarl.europa.eu/RegData/etudes/STUD/2024/762854/EPRS_STU\(2024\)762854_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2024/762854/EPRS_STU(2024)762854_EN.pdf)
- European Union (2012), Consolidated version of the Treaty on European Union. Official Journal of the European Union, C 326. Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A12012M%2FTXT>
- European Union (2012), Consolidated version of the Treaty on the Functioning of the European Union. Official Journal of the European Union, C 326. Available at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A12012E%2FTXT>
- Eurostat (2021), Glossary: Young people neither in employment nor in education and training (NEET). European Commission. Available at: <https://ec.europa.eu/eurostat/statistics-explained/SEPDF/cache/11889.pdf>
- Eurostat (2025), Eurostat regional yearbook. European Commission. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Eurostat_regional_yearbook
- Eurostat (2025), National accounts and GDP. European Commission. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=National_accounts_and_GDP
- Eurostat (2025), Statistics on young people neither in employment nor in education or training. European Commission. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Statistics_on_young_people_neither_in_employment_nor_in_education_or_training

- Eurostat (2026), Economy at regional level. European Commission. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Economy_at_regional_level
- Eurostat (2026), Education and training statistics at regional level. European Commission. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Education_and_training_statistics_at_regional_level
- Eurostat (2026), Glossary: GDP per capita in purchasing power standards. European Commission. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:GDP_per_capita_in_purchasing_power_standards
- Eurostat (2026), Glossary: Purchasing power parities (PPPs). European Commission. Available at: [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Purchasing_power_parities_\(PPPs\)](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Purchasing_power_parities_(PPPs))
- Eurostat (2026), NUTS - Nomenclature of territorial units for statistics. European Commission. Available at: <https://ec.europa.eu/eurostat/web/nuts>
- Eurostat (2026), Principles - NUTS - Nomenclature of territorial units for statistics. European Commission. Available at: <https://ec.europa.eu/eurostat/web/nuts/principles>
- Faridi, R. (2019) Backwash Effect: Economic Development and Regional Inequality. Available at: <https://rashidfaridi.com/2019/04/30/backwash-effect-economic/>
- Ferrant, G. (2014), The Multidimensional Gender Inequalities Index (MGII): A Descriptive Analysis of Gender Inequalities Using MCA. Social Indicators Research. Available at: <https://ideas.repec.org/a/spr/soinre/v115y2014i2p653-690.html>
- Fischer, M.M. and Stirböck, C. (2004), Regional Income Convergence in the Enlarged Europe, 1995-2000: A Spatial Econometric Perspective. ZEW Discussion Papers. Available at: <https://www.zew.de/fileadmin/FTP/dp/dp0442.pdf>
- Fratesi, U. and Perucca, G. (2014), Territorial capital and the effectiveness of cohesion policies: an assessment for CEE regions. Investigaciones Regionales. Available at: <https://ideas.repec.org/a/ris/invreg/0267.html>
- Fundación Yuste (2025), Orientation of the Call: Annex III. Rationale and context of the call. Fundación Yuste. Available at: <https://www.fundacionyuste.org/wp-content/uploads/2025/01/OrientationoftheCallMerkel2025.pdf>
- Gagliardi, L. and Percoco, M. (2017), The impact of European Cohesion Policy in urban and rural regions. Taylor & Francis. Available at: <https://ideas.repec.org/a/taf/regstd/v51y2017i6p857-868.html>
- Gjøstein, D.K. (2026), Updating the Regional Authority Index (RAI) for the European Commission. Department of Comparative Politics, University of Bergen. Available at: <https://www.uib.no/en/sampol/181579/Updating-regional-authority-index-rai-european-commission>
- Goecke, H. and Hüther, M. (2016), Regional convergence in Europe. Intereconomics. Available at: <https://www.intereconomics.eu/contents/year/2016/number/3/article/regional-convergence-in-europe.html>
- Gräbner, C. et al. (2020), Pandemic pushes polarisation: The COVID-19 crisis and macroeconomic divergence in the Eurozone. Journal of Industrial and Business Economics. Available at: <https://pmc.ncbi.nlm.nih.gov/articles/PMC7347665/>

- European Commission (2026), Directorate-General for Regional and Urban Policy. Available at: https://ec.europa.eu/regional_policy/home_en
- Hervás-Oliver, J.L., Parrilli, M.D., Rodríguez-Pose, A. and Sempere-Ripoll, F. (2021), The drivers of SME innovation in the regions of the EU. Research Policy. Available at: <https://www.sciencedirect.com/science/article/pii/S0048733321001177>
- Hooghe, L. and Marks, G. (2016), Measuring Regional Authority: A Postfunctionalist Theory of Governance, Volume I. Oxford University Press. Available at: https://garymarks.web.unc.edu/wp-content/uploads/sites/13018/2021/03/Hooghe_Marks_Schakel_Niedzwiecki_Osterkatz_Shairrosenfield_Measuring-regional-authority_2016.pdf
- Hsieh, C.T. and Klenow, P.J. (2010), Development Accounting. American Economic Journal: Macroeconomics. Available at: <https://www.aeaweb.org/articles?id=10.1257/mac.2.1.207>
- Iammarino, S. et al. (2020), Falling into the Middle-Income Trap? A Study on the Risks for EU Regions to be Caught in a Middle-Income Trap. Publications Office of the European Union. Available at: <https://doi.org/10.2776/02363>
- Jones, C.I. (2002), Introduction to Economic Growth. W.W. Norton & Company. Available at: https://joseordinola2014.wordpress.com/wp-content/uploads/2014/11/jones_crecimiento-economico.pdf
- Kalavros, V. and Georgopoulos, T. (2013), European Union Law. Nomiki Bibliothiki. Available at: <https://abstracts.nb.org/2192/files/assets/basic-html/page6.html>
- Kaldor, N. (1989), The Role of Increasing Returns, Technical Progress and Cumulative Causation in the Theory of International Trade and Economic Growth (in F. Targetti and A.P. Thirlwall, eds., The Essential Kaldor). Gerald Duckworth. Available at: https://www.persee.fr/doc/ecoap_0013-0494_1981_num_34_4_4324
- Krugman, P. (1991), Increasing Returns and Economic Geography. Journal of Political Economy. Available at: <https://doi.org/10.1086/261763>
- Laird, J.J., Nellthorp, J. and Mackie, P.J. (2005), Network effects and total economic impact in transport appraisal. Transport Policy. Available at: https://www.researchgate.net/publication/23528183_Network_effects_and_total_economic_impact_in_transport_appraisal
- Lambovska, M., et al. (2021), Impact of Covid-19 Pandemic on the Youth Unemployment in the European Union. Economic and Managerial Spectrum. Available at: https://ems.uniza.sk/pdf/2021_1/EMS_1_2021_05_Lambovska_Sardinha_BelasJr.pdf
- Le Gallo, J., Dall'Erba, S. and Guillain, R. (2011), The Local versus Global Dilemma of the Effects of Structural Funds. Growth and Change. Available at: <https://doi.org/10.1111/j.1468-2257.2011.00564.x>
- LeSage, J. and Pace, R.K. (2009), Introduction to Spatial Econometrics. Chapman and Hall/CRC. Available at: <https://www.taylorfrancis.com/books/mono/10.1201/9781420064254/introduction-spatial-econometrics-james-lesage-robert-kelley-pace>
- Mankiw, N.G., Romer, D. and Weil, D.N. (1992), A Contribution to the Empirics of Economic Growth. The Quarterly Journal of Economics. Available at: <https://academic.oup.com/qje/article-abstract/107/2/407/1838296?redirectedFrom=fulltext&login=false>

- Martinho, V. D. (2021). Impact of COVID-19 on the convergence of GDP per capita in OECD countries. *Regional Science Policy & Practice*, 13(S1), 55–72. Available at: <https://www.sciencedirect.com/science/article/pii/S175778022300570X?via%3Dihub>
- Marzinotto, B. (2012), The growth effects of EU cohesion policy: A meta-analysis. Bruegel. Available at: <https://www.bruegel.org/working-paper/growth-effects-eu-cohesion-policy-meta-analysis>
- Mazzucato, M. (2014), The Entrepreneurial State: Debunking Public vs. Private Sector Myths. Anthem Press. Available at: https://www.researchgate.net/publication/279930695_The_Entrepreneurial_State_Debunking_Private_vs_Public_Sector_Myths
- McCann, P. (2015), The Regional and Urban Policy of the European Union: Cohesion, Results-Oriented and Smart Specialisation. Edward Elgar Publishing. Available at: https://www.researchgate.net/publication/284636174_The_Regional_and_Urban_Policy_of_the_European_Union_Cohesion_Result-orientation_and_Smart_Specialisation
- Medeiros, E., Zauha, J. and Ciolek, D. (2021), Measuring territorial cohesion trends in Europe: A correlation with EU Cohesion Policy. *European Planning Studies*. Available at: https://scholar.google.com/citations?view_op=view_citation&hl=pl&user=CxK5RIIAAAAJ&citation_for_view=CxK5RIIAAAAJ:u3T1itk59dMC
- Miladinov, G. (2020), Socioeconomic development and life expectancy relationship: evidence from the EU accession candidate countries. *Genus*, 76, article 2. Available at: <https://doi.org/10.1186/s41118-019-0071-0>
- Mohl, P. and Hagen, T. (2008), Does EU cohesion policy promote growth? Evidence from regional data and alternative econometric approaches. *ZEW Discussion Papers*. Available at: <https://ftp.zew.de/pub/zew-docs/dp/dp08086.pdf>
-
- Molica, F. and Santos, E. (2020), Mapping uncharted territory: research gaps in EU cohesion policy from a policy-making perspective. *Regional Studies*. Available at: <https://www.tandfonline.com/doi/full/10.1080/21681376.2025.2514503>
- Molle, W. (2006), The Economics of European Integration: Theory, Practice, Policy. Ashgate. Available at: https://books.google.fr/books/about/The_Economics_of_European_Integration.html?id=XLDeOlqKlwwC&redir_esc=y
- Mongey, S., Pilossoph, L. and Weinberg, A. (2020), Which Workers Bear the Burden of Social Distancing?. *National Bureau of Economic Research*. Available at: <https://pubmed.ncbi.nlm.nih.gov/34366750/>
- Montfort, P. (2008), Convergence of EU regions - Measures and evolution. *European Union Regional Policy Working Papers*. Available at: https://ec.europa.eu/regional_policy/sources/work/022020_convergence_redux.pdf
- Moreno, R. (2020), EU Cohesion Policy Performance: Regional Variation and the Role of Innovation. *Regional Studies*. Available at: <https://investigacionesregionales.org/en/article/eu-cohesion-policy-performance-regional-variation-in-the-effectiveness-of-the-management-of-the-structural-funds/>
- Muggenthaler, P., Schroth, J. and Sun, Y. (2021), The heterogeneous economic impact of the pandemic across euro area countries. *ECB Economic Bulletin*. Available at: https://www.ecb.europa.eu/press/economic-bulletin/focus/2021/html/ecb.ebbox202105_03~267ada0d38.en.html

- Myrdal, G. (1957), *Economic Theory and Under-developed Regions*. Gerald Duckworth. Available at: <https://www.scirp.org/reference/referencespapers?referenceid=2273735>
- North, D.C. (1990), *Institutions, Institutional Change and Economic Performance*. Cambridge University Press. Available at: <https://www.cambridge.org/core/books/institutions-institutional-change-and-economic-performance/AAE1E27DF8996E24C5DD07EB79BBA7EE>
- OECD (2019), *OECD Regional Outlook 2019: Leveraging Megatrends for Cities and Rural Areas*. OECD Publishing. Available at: <https://doi.org/10.1787/9789264312838-en>
- OECD (2023), *OECD Compendium of Productivity Indicators 2023*. OECD Publishing. Available at: <https://doi.org/10.1787/74623e5b-en>
- OECD (2024), *Education, economic and social outcomes*. OECD Publishing. Available at: <https://www.oecd.org/en/topics/education-economic-and-social-outcomes.html>
- OECD (2025), *Health at a Glance 2025: OECD Indicators*. OECD Publishing. Available at: <https://doi.org/10.1787/8f9e3f98-en>
- OECD (2026), *Employment rate by age group*. OECD Publishing. Available at: <https://www.oecd.org/en/data/indicators/employment-rate-by-age-group.html>
- Paas, T. et al. (2007), *Econometric assessments of Cohesion Policy growth effects*. European Economy - Economic Papers. Available at: <https://www.taylorfrancis.com/chapters/oa-edit/10.4324/9781315401867-5/econometric-assessments-cohesion-policy-growth-effects-jerzy-pie%C5%84kowski-peter-berkowitz>
- Pellegrini, G. et al. (2013), *Measuring the effects of European Regional Policy on economic growth: A regression discontinuity approach*. Papers in Regional Science. Available at: <https://doi.org/10.1111/j.1435-5957.2012.00459.x>
- Pereira, A.M. and Roca-Sagalés, O. (2003), *Spillover effects of public capital formation: evidence from the Spanish regions*. Journal of Urban Economics. Available at: <https://www.sciencedirect.com/science/article/abs/pii/S009411900200517X>
- Perrons, D. (2011), *Regional performance and inequality: linking economic and social development through a capabilities approach*. Cambridge Journal of Regions, Economy and Society. Available at: <https://academic.oup.com/cjres/article-abstract/5/1/15/325956>
- Pieńkowski, J. and Berkowitz, P. (2015), *Econometric assessments of Cohesion Policy growth effects: How to make them more relevant for policy makers?*. European Commission. Available at: <https://www.taylorfrancis.com/chapters/oa-edit/10.4324/9781315401867-5/econometric-assessments-cohesion-policy-growth-effects-jerzy-pie%C5%84kowski-peter-berkowitz>
- Potrafke, N. (2010), *Does government ideology influence deregulation of product markets? Empirical evidence from OECD countries*. Public Choice. Available at: <https://link.springer.com/article/10.1007/s11127-009-9494-z>
- Puga, D. (2002), *European regional policies in light of recent location theories*. Journal of Economic Geography. Available at: <https://doi.org/10.1093/jeg/2.4.373>
- Quah, D. (1993), *Empirical cross-section dynamics in economic growth*. European Economic Review. Available at: <https://www.sciencedirect.com/science/article/abs/pii/0014292193900315>
- Rodríguez-Pose, A. (2025) *Forging a sustainable future together: Cohesion Policy at its defining moment, Regional Studies*. Available at:

<https://www.tandfonline.com/doi/epdf/10.1080/00343404.2025.2552869?needAccess=true>

- Rodríguez-Pose (2024). Group of High-Level Specialists on the Future of Cohesion Policy , Forging a sustainable future together: report of the High-Level Group on the Future of Cohesion Policy. Group of High-Level Specialists on the Future of Cohesion Policy. Available at: <https://cepr.org/voxeu/columns/forging-sustainable-future-together-report-high-level-group-future-cohesion-policy>
- Rodríguez-Pose, A. and Crescenzi, R. (2008), Research and development, spillovers, innovation systems, and the genesis of regional growth in Europe. *Regional Studies*. Available at: <https://doi.org/10.1080/00343400701654186>
- Rodríguez-Pose, A. and Fratesi, U. (2004), Between development and social policies: The impact of European Structural Funds in Objective 1 regions. *Regional Studies*. Available at: <https://www.tandfonline.com/doi/abs/10.1080/00343400310001632226>
- Rodríguez-Pose, A. and Garcilazo, E. (2015), Quality of Government and the Returns of Investment: Examining the Impact of Cohesion Expenditure in European Regions. *Regional Studies*. Available at: <https://doi.org/10.1080/00343404.2015.1007933>
- Romer, P.M. (1986), Increasing Returns and Long-Run Growth. *Journal of Political Economy*. Available at: <https://doi.org/10.1086/261420>
- Romer, P.M. (1990), Endogenous Technological Change. *Journal of Political Economy*. Available at: <https://doi.org/10.1086/261725>
- Solow, R.M. (1956), A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*. Available at: <https://doi.org/10.2307/1884513>
- Swan, T.W. (1956), Economic Growth and Capital Accumulation. *Economic Record*. Available at: <https://doi.org/10.1111/j.1475-4932.1956.tb00434.x>
- UNDP (2026), Human Development Index. United Nations Development Programme. Available at: <https://hdr.undp.org/data-center/human-development-index>
- University of Gothenburg (2026), QoG Data. The QoG Institute. Available at: <https://www.gu.se/en/quality-government/qog-data>
- Venables, A.J. (2005), Spatial Disparities in Developing Countries: Cities, Regions, and International Trade. *Journal of Economic Geography*. Available at: <https://www.jstor.org/stable/26160603>
- World Health Organization (2025), Life expectancy at birth (years). data.who.int. Available at: <https://data.who.int/indicators/i/A21CFC2/90E2E48>

APPENDIX A: ABSOLUTE BETA CONVERGENCE RESULTS

This appendix reports the OLS estimates of the absolute β -convergence model for all indicators considered in the analysis. For each variable, the dependent variable is the average annual growth rate over the period, while the explanatory variable is the logarithm of the initial level. Results are reported for two alternative time spans (2014–2019 and 2014–2020) as a robustness check. Scatter plots with fitted regression lines are also provided to visually assess the presence of β -convergence.

A1. Absolute β -convergence — GDP per capita (PPS), 2014–2019 (OLS)

RESULTS BETA-CONVERGENZA (2014-2019)

OLS Regression Results

Dep. Variable:	g_14_19	R-squared:	0.120
Model:	OLS	Adj. R-squared:	0.116
Method:	Least Squares	F-statistic:	32.92
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	2.86e-08
Time:	18:01:05	Log-Likelihood:	652.00
No. Observations:	244	AIC:	-1300.
Df Residuals:	242	BIC:	-1293.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	0.0682	0.012	5.625	0.000	0.044	0.092
ln_X0	-0.0155	0.003	-5.737	0.000	-0.021	-0.010

Omnibus:	136.056	Durbin-Watson:	1.040
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2296.437
Skew:	1.781	Prob(JB):	0.00
Kurtosis:	17.601	Cond. No.	53.2

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A2. Absolute β -convergence — GDP per capita (PPS), 2014–2020 (OLS)

=====

RESULTS BETA-CONVERGENZA (2014–2020)

=====

OLS Regression Results

=====

Dep. Variable:	g_14_20	R-squared:	0.094
Model:	OLS	Adj. R-squared:	0.090
Method:	Least Squares	F-statistic:	25.18
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	1.01e-06
Time:	18:01:07	Log-Likelihood:	626.15
No. Observations:	244	AIC:	-1248.
Df Residuals:	242	BIC:	-1241.
Df Model:	1		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0667	0.013	4.948	0.000	0.040	0.093
ln_X0	-0.0150	0.003	-5.018	0.000	-0.021	-0.009

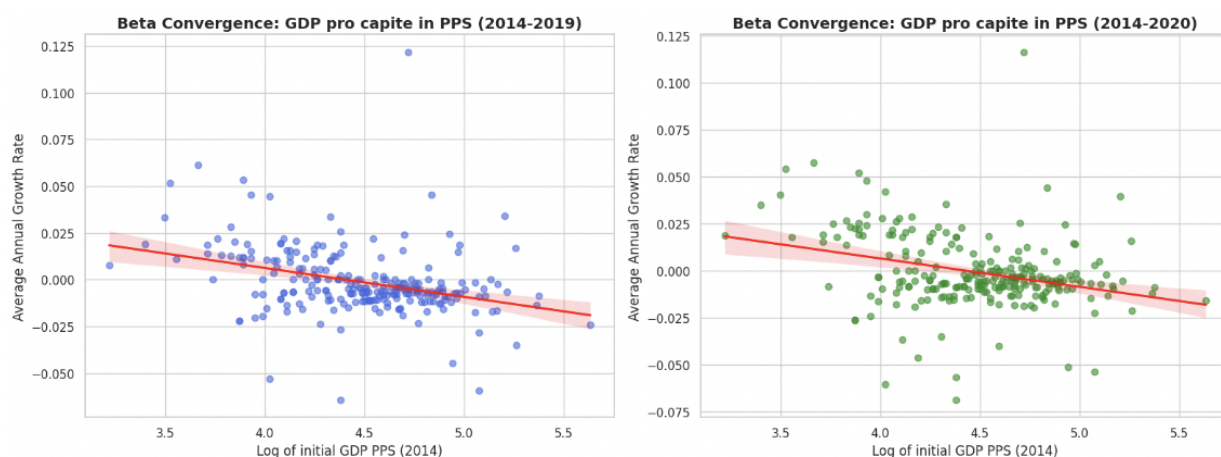
=====

Omnibus:	68.897	Durbin-Watson:	0.792
Prob(Omnibus):	0.000	Jarque-Bera (JB):	717.280
Skew:	0.751	Prob(JB):	1.76e-156
Kurtosis:	11.264	Cond. No.	53.2

Note: OLS estimates of the absolute β -convergence model for the period 2014-2020. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A3. Graph absolute β -convergence — GDP per capita (PPS)



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of GDP per capita across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

A4. Absolute β -convergence — Labour productivity, 2014–2019 (OLS)

RESULTS BETA-CONVERGENZA (2014-2019)						
OLS Regression Results						
Dep. Variable:	g_14_19	R-squared:	0.131			
Model:	OLS	Adj. R-squared:	0.128			
Method:	Least Squares	F-statistic:	35.12			
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	1.11e-08			
Time:	18:02:06	Log-Likelihood:	586.26			
No. Observations:	234	AIC:	-1169.			
Df Residuals:	232	BIC:	-1162.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.2734	0.043	6.409	0.000	0.189	0.357
ln_X0	-0.0231	0.004	-5.926	0.000	-0.031	-0.015
Omnibus:	67.075	Durbin-Watson:	1.216			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1046.937			
Skew:	0.598	Prob(JB):	4.58e-228			
Kurtosis:	13.293	Cond. No.	363.			

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

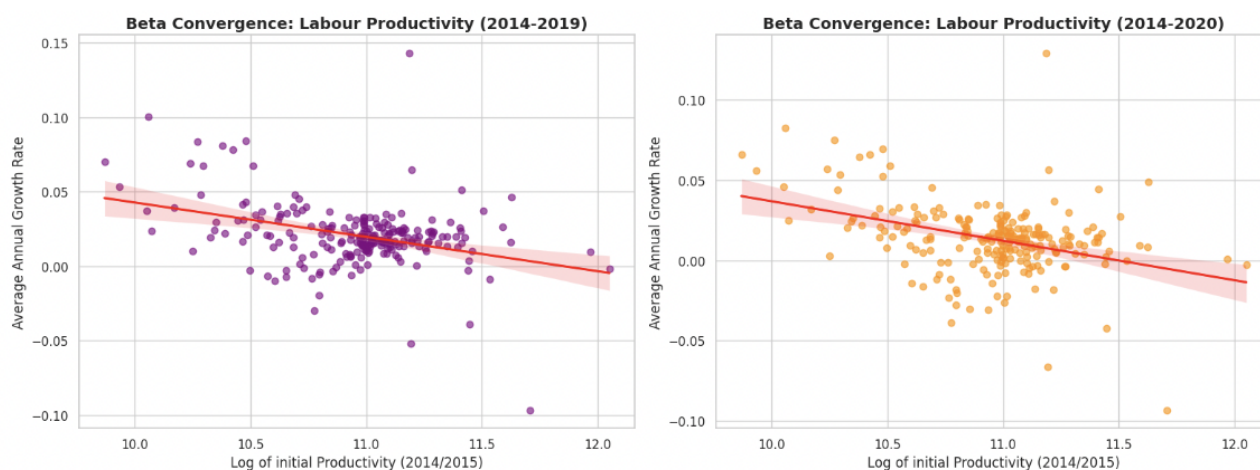
A5. Absolute β -convergence — Labour productivity, 2014–2020 (OLS)

RESULTS BETA-CONVERGENZA (2014-2020)						
OLS Regression Results						
Dep. Variable:	g_14_20	R-squared:	0.139			
Model:	OLS	Adj. R-squared:	0.135			
Method:	Least Squares	F-statistic:	37.44			
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	3.98e-09			
Time:	18:02:06	Log-Likelihood:	578.49			
No. Observations:	234	AIC:	-1153.			
Df Residuals:	232	BIC:	-1146.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.2832	0.044	6.422	0.000	0.196	0.370
ln_X0	-0.0246	0.004	-6.119	0.000	-0.033	-0.017
Omnibus:	44.706	Durbin-Watson:	1.016			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	456.234			
Skew:	0.259	Prob(JB):	8.51e-100			
Kurtosis:	9.821	Cond. No.	363.			

Note: OLS estimates of the absolute β -convergence model for the period 2014-2020. A negative and statistically significant coefficient on $\ln_X0$ indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A6. Graph absolute β -convergence



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of labour productivity. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

A7. Absolute β -convergence — Employment in technology and science, 2014–2019 (OLS)

RESULTS BETA-CONVERGENZA (2014-2019)						
OLS Regression Results						
Dep. Variable:	g_14_19		R-squared:	0.338		
Model:	OLS		Adj. R-squared:	0.336		
Method:	Least Squares		F-statistic:	138.5		
Date:	Sat, 11 Apr 2026		Prob (F-statistic):	4.22e-26		
Time:	18:02:51		Log-Likelihood:	747.92		
No. Observations:	273		AIC:	-1492.		
Df Residuals:	271		BIC:	-1485.		
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.1430	0.010	13.789	0.000	0.123	0.163
ln_X0	-0.0339	0.003	-11.768	0.000	-0.040	-0.028
Omnibus:	75.104		Durbin-Watson:	1.602		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	849.967		
Skew:	0.719		Prob(JB):	2.70e-185		
Kurtosis:	11.524		Cond. No.	42.3		

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

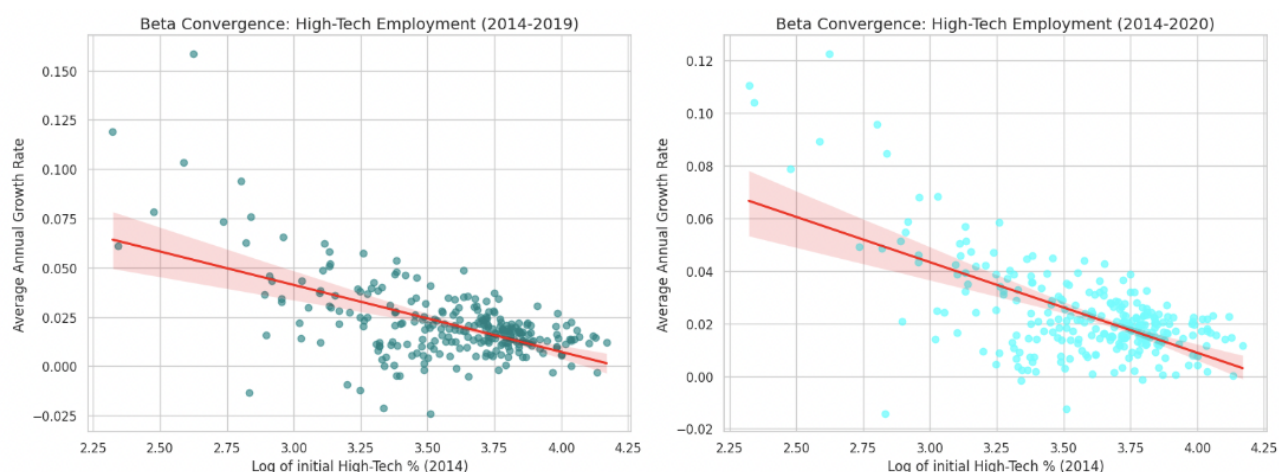
A8. Absolute β -convergence — Employment in technology and science, 2014–2020 (OLS)

RESULTS BETA-CONVERGENZA (2014-2020)						
OLS Regression Results						
Dep. Variable:	g_14_20	R-squared:	0.404			
Model:	OLS	Adj. R-squared:	0.402			
Method:	Least Squares	F-statistic:	183.8			
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	2.62e-32			
Time:	18:02:51	Log-Likelihood:	782.47			
No. Observations:	273	AIC:	-1561.			
Df Residuals:	271	BIC:	-1554.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.1466	0.009	16.042	0.000	0.129	0.165
ln_X0	-0.0344	0.003	-13.555	0.000	-0.039	-0.029
Omnibus:	28.964	Durbin-Watson:	1.221			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	148.932			
Skew:	0.025	Prob(JB):	4.57e-33			
Kurtosis:	6.618	Cond. No.	42.3			

Note: OLS estimates of the absolute β -convergence model for the period 2014-2020. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A9. Graph β -convergence — Employment in technology and science



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of high tech employment across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

A10. Absolute β -convergence — Life expectancy, 2014–2019 (OLS)

=====

RESULTS BETA-CONVERGENZA (2014-2019)

=====

OLS Regression Results

=====

Dep. Variable:	g_14_19	R-squared:	0.049
Model:	OLS	Adj. R-squared:	0.045
Method:	Least Squares	F-statistic:	12.34
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	0.000532
Time:	18:03:40	Log-Likelihood:	1314.0
No. Observations:	240	AIC:	-2624.
Df Residuals:	238	BIC:	-2617.
Df Model:	1		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0319	0.009	3.636	0.000	0.015	0.049
ln_X0	-0.0070	0.002	-3.512	0.001	-0.011	-0.003

=====

Omnibus:	16.862	Durbin-Watson:	1.142
Prob(Omnibus):	0.000	Jarque-Bera (JB):	35.624
Skew:	0.317	Prob(JB):	1.84e-08
Kurtosis:	4.778	Cond. No.	617.

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

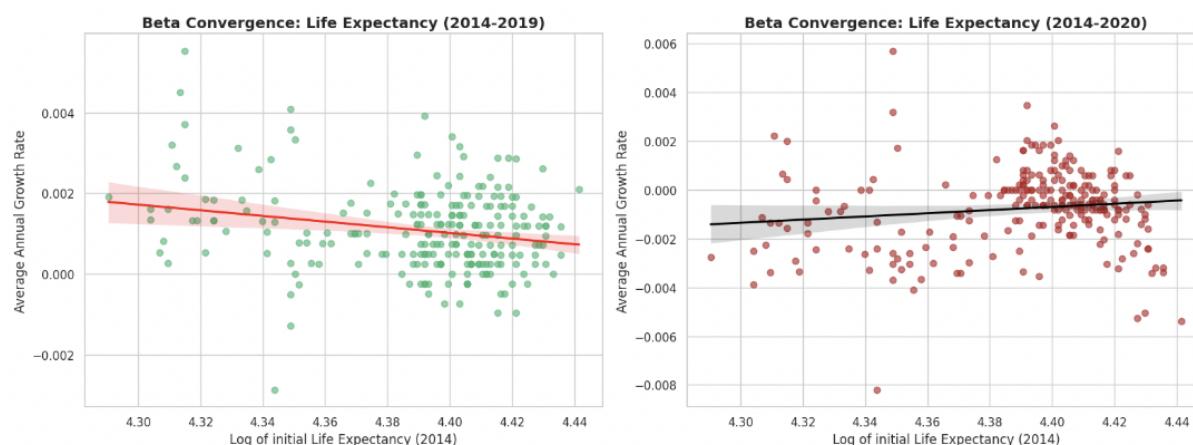
A11. Absolute β -convergence — Life expectancy, 2014–2020 (OLS)

RESULTS BETA-CONVERGENZA (2014-2020)						
OLS Regression Results						
Dep. Variable:	g_14_20		R-squared:	0.017		
Model:	OLS		Adj. R-squared:	0.013		
Method:	Least Squares		F-statistic:	4.167		
Date:	Sat, 11 Apr 2026		Prob (F-statistic):	0.0423		
Time:	18:03:40		Log-Likelihood:	1201.8		
No. Observations:	240		AIC:	-2400.		
Df Residuals:	238		BIC:	-2393.		
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-0.0294	0.014	-2.096	0.037	-0.057	-0.002
ln_X0	0.0065	0.003	2.041	0.042	0.000	0.013
Omnibus:	21.046		Durbin-Watson:	0.982		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	64.688		
Skew:	-0.255		Prob(JB):	8.98e-15		
Kurtosis:	5.492		Cond. No.	617.		

Note: OLS estimates of the absolute β -convergence model for the period 2014–2020. A negative and statistically significant coefficient on $\ln_X0$ indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A12. Graph β -convergence — Life expectancy



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of life expectancy across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence, while the positive indicates divergence.

Source: Author's elaboration based on Eurostat regional data.

A12. Absolute β -convergence — Tertiary education level, 2014–2019 (OLS)

RESULTS BETA-CONVERGENZA (2014-2019)						
OLS Regression Results						
Dep. Variable:	g_14_19		R-squared:	0.038		
Model:	OLS		Adj. R-squared:	0.034		
Method:	Least Squares		F-statistic:	9.538		
Date:	Sat, 11 Apr 2026		Prob (F-statistic):	0.00225		
Time:	18:04:31		Log-Likelihood:	614.58		
No. Observations:	243		AIC:	-1225.		
Df Residuals:	241		BIC:	-1218.		
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0641	0.013	5.076	0.000	0.039	0.089
ln_X0	-0.0119	0.004	-3.088	0.002	-0.020	-0.004
Omnibus:	95.011	Durbin-Watson:	2.143			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1955.375			
Skew:	-0.976	Prob(JB):	0.000			
Kurtosis:	16.759	Cond. No.	36.3			

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A13. Absolute β -convergence — Tertiary education level, 2014–2020 (OLS)

=====

RESULTS BETA-CONVERGENZA (2014–2020)

=====

OLS Regression Results

=====

Dep. Variable:	g_14_20	R-squared:	0.024
Model:	OLS	Adj. R-squared:	0.020
Method:	Least Squares	F-statistic:	6.018
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	0.0149
Time:	18:04:31	Log-Likelihood:	647.06
No. Observations:	243	AIC:	-1290.
Df Residuals:	241	BIC:	-1283.
Df Model:	1		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0542	0.011	4.909	0.000	0.032	0.076
ln_X0	-0.0083	0.003	-2.453	0.015	-0.015	-0.002

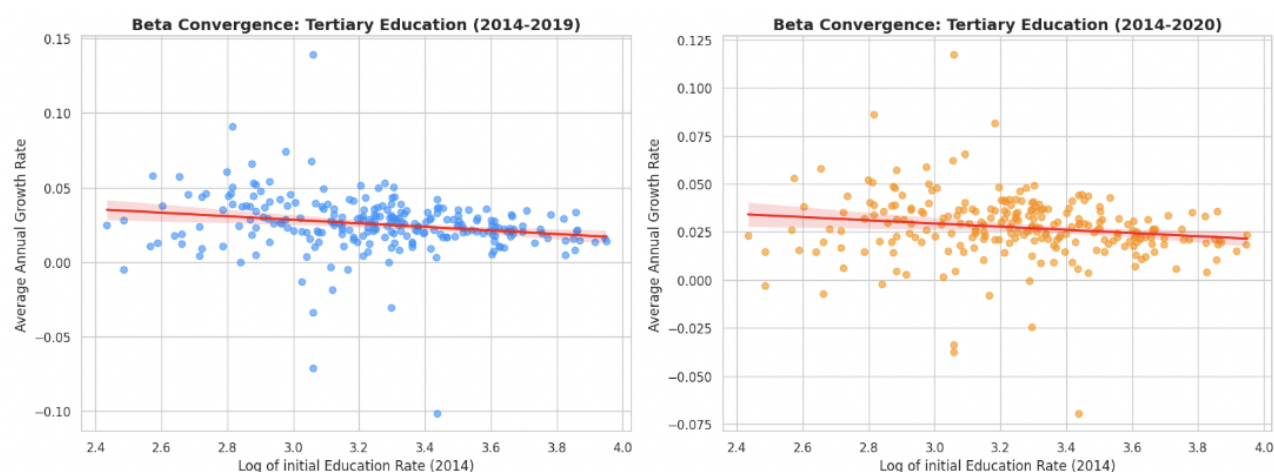
=====

Omnibus:	59.529	Durbin-Watson:	1.913
Prob(Omnibus):	0.000	Jarque-Bera (JB):	709.433
Skew:	-0.520	Prob(JB):	8.88e-155
Kurtosis:	11.306	Cond. No.	36.3

Note: OLS estimates of the absolute β -convergence model for the period 2014-2020. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A14. Graph β -convergence — Tertiary education level



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of tertiary education attained across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

A15. Absolute β -convergence — NEET rate, 2014–2019 (OLS)

RESULTS BETA-CONVERGENZA (2014-2019)						
OLS Regression Results						
Dep. Variable:	g_14_19		R-squared:	0.076		
Model:	OLS		Adj. R-squared:	0.072		
Method:	Least Squares		F-statistic:	19.77		
Date:	Sat, 11 Apr 2026		Prob (F-statistic):	1.33e-05		
Time:	18:05:21		Log-Likelihood:	443.46		
No. Observations:	242		AIC:	-882.9		
Df Residuals:	240		BIC:	-875.9		
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0178	0.014	1.281	0.201	-0.010	0.045
ln_x0	-0.0231	0.005	-4.447	0.000	-0.033	-0.013
Omnibus:	6.594		Durbin-Watson:	1.291		
Prob(Omnibus):	0.037		Jarque-Bera (JB):	10.460		
Skew:	-0.048		Prob(JB):	0.00535		
Kurtosis:	4.014		Cond. No.	17.0		

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A16. Absolute β -convergence — NEET rate, 2014–2020 (OLS)

=====

RESULTS BETA-CONVERGENZA (2014-2020)

=====

OLS Regression Results

=====

Dep. Variable:	g_14_20	R-squared:	0.154
Model:	OLS	Adj. R-squared:	0.150
Method:	Least Squares	F-statistic:	43.54
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	2.63e-10
Time:	18:05:21	Log-Likelihood:	468.76
No. Observations:	242	AIC:	-933.5
Df Residuals:	240	BIC:	-926.5
Df Model:	1		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0623	0.013	4.967	0.000	0.038	0.087
ln_X0	-0.0308	0.005	-6.599	0.000	-0.040	-0.022

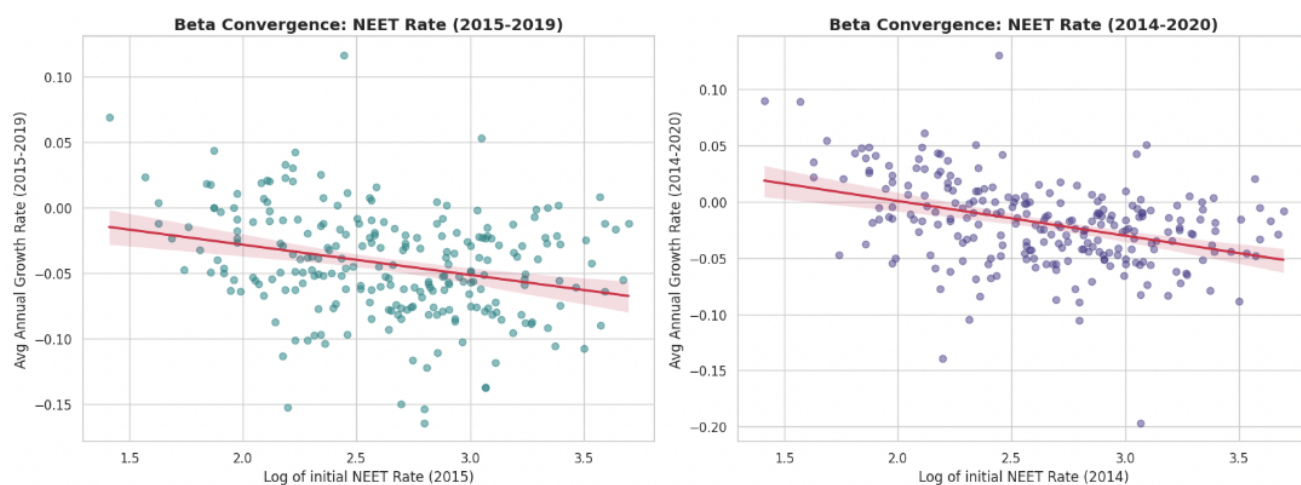
=====

Omnibus:	30.575	Durbin-Watson:	1.268
Prob(Omnibus):	0.000	Jarque-Bera (JB):	99.083
Skew:	-0.465	Prob(JB):	3.05e-22
Kurtosis:	5.994	Cond. No.	17.0

Note: OLS estimates of the absolute β -convergence model for the period 2014–2020. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A17. Graph β -convergence — NEET rate



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of NEET rate across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

A18. Absolute β -convergence — Employment rate, 2014–2019 (OLS)

RESULTS BETA-CONVERGENZA (2014-2019)						
OLS Regression Results						
Dep. Variable:	g_14_19		R-squared:	0.142		
Model:	OLS		Adj. R-squared:	0.138		
Method:	Least Squares		F-statistic:	39.86		
Date:	Sat, 11 Apr 2026		Prob (F-statistic):	1.30e-09		
Time:	18:06:09		Log-Likelihood:	814.67		
No. Observations:	243		AIC:	-1625.		
Df Residuals:	241		BIC:	-1618.		
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.1090	0.016	6.931	0.000	0.078	0.140
ln_X0	-0.0249	0.004	-6.314	0.000	-0.033	-0.017
Omnibus:	8.237		Durbin-Watson:	1.049		
Prob(Omnibus):	0.016		Jarque-Bera (JB):	12.062		
Skew:	-0.202		Prob(JB):	0.00240		
Kurtosis:	4.014		Cond. No.	122.		

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A19. Absolute β -convergence — Employment rate, 2014–2020 (OLS)

=====

RESULTS BETA-CONVERGENZA (2014–2020)

=====

OLS Regression Results

=====

Dep. Variable:	g_14_20	R-squared:	0.149
Model:	OLS	Adj. R-squared:	0.145
Method:	Least Squares	F-statistic:	42.12
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	4.85e-10
Time:	18:06:09	Log-Likelihood:	844.61
No. Observations:	243	AIC:	-1685.
Df Residuals:	241	BIC:	-1678.
Df Model:	1		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0960	0.014	6.905	0.000	0.069	0.123
ln_X0	-0.0227	0.003	-6.490	0.000	-0.030	-0.016

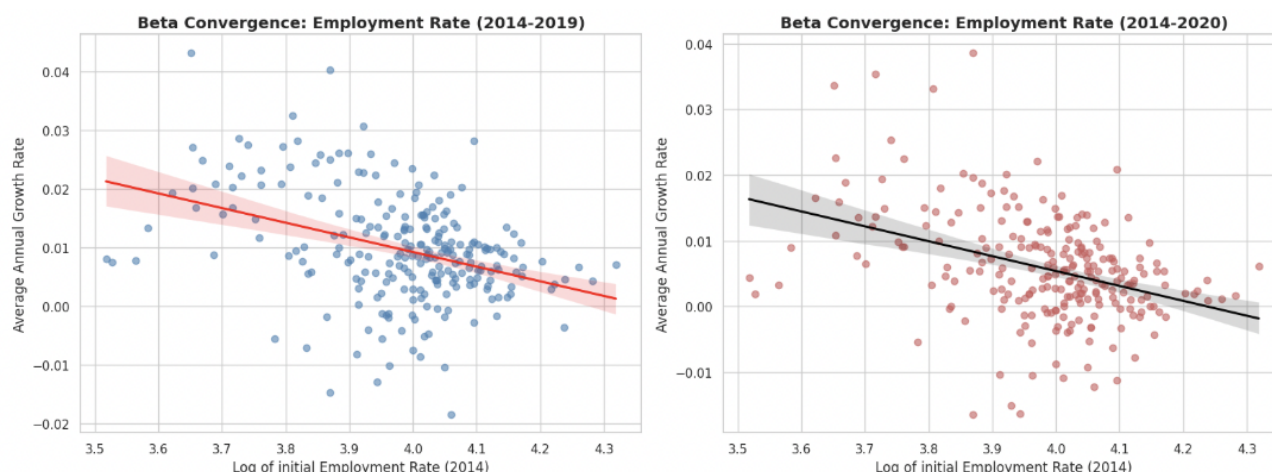
=====

Omnibus:	14.209	Durbin-Watson:	1.353
Prob(Omnibus):	0.001	Jarque-Bera (JB):	36.621
Skew:	0.091	Prob(JB):	1.12e-08
Kurtosis:	4.893	Cond. No.	122.

Note: OLS estimates of the absolute β -convergence model for the period 2014-2020. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A20. Graph β -convergence — Employment rate



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of employment rate across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

A21. Absolute β -convergence — Gender employment gap, 2014–2019 (OLS)

RESULTS NACE BETA-CONVERGENCE (2014-2019)						
OLS Regression Results						
Dep. Variable:	g_15_19		R-squared:	0.005		
Model:	OLS		Adj. R-squared:	0.001		
Method:	Least Squares		F-statistic:	1.149		
Date:	Sat, 11 Apr 2026		Prob (F-statistic):	0.285		
Time:	18:28:56		Log-Likelihood:	673.90		
No. Observations:	236		AIC:	-1344.		
Df Residuals:	234		BIC:	-1337.		
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0183	0.006	2.873	0.004	0.006	0.031
ln_X0	-0.0011	0.001	-1.072	0.285	-0.003	0.001
Omnibus:	38.231		Durbin-Watson:	1.509		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	217.614		
Skew:	-0.407		Prob(JB):	5.57e-48		
Kurtosis:	7.633		Cond. No.	45.7		

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A22. Absolute β -convergence — Gender employment gap, 2014–2020 (OLS)

RESULTS NACE BETA-CONVERGENCE (2014-2020)

OLS Regression Results

Dep. Variable:	g_15_20	R-squared:	0.003
Model:	OLS	Adj. R-squared:	-0.001
Method:	Least Squares	F-statistic:	0.8149
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	0.368
Time:	18:28:56	Log-Likelihood:	697.31
No. Observations:	236	AIC:	-1391.
Df Residuals:	234	BIC:	-1384.
Df Model:	1		
Covariance Type:	nonrobust		

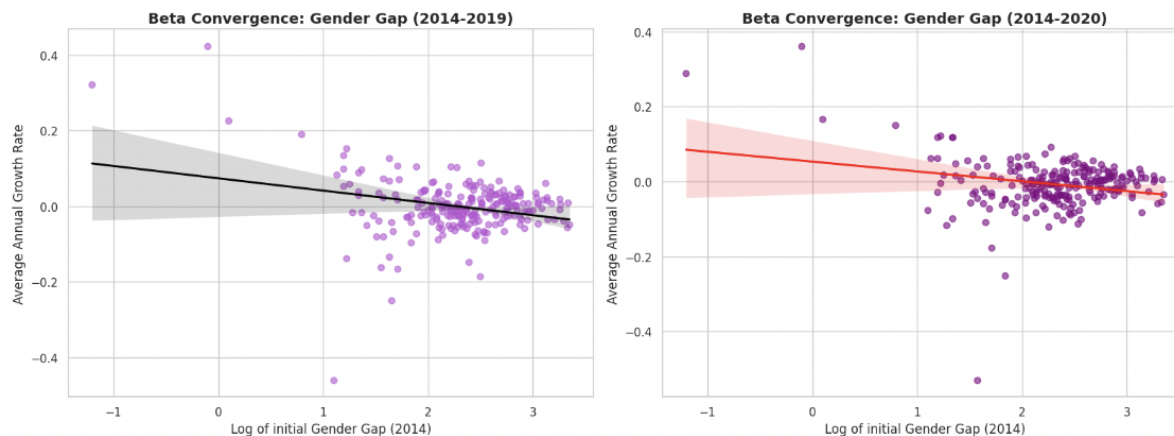
	coef	std err	t	P> t	[0.025	0.975]
const	0.0112	0.006	1.932	0.055	-0.000	0.023
ln_X0	-0.0008	0.001	-0.903	0.368	-0.003	0.001

Omnibus:	18.649	Durbin-Watson:	1.615
Prob(Omnibus):	0.000	Jarque-Bera (JB):	64.458
Skew:	-0.015	Prob(JB):	1.01e-14
Kurtosis:	5.560	Cond. No.	45.7

Note: OLS estimates of the absolute β -convergence model for the period 2014-2020. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A23. Graph β -convergence — Gender employment gap



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of gender gap across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

A24. Absolute β -convergence — Structural composition of the economy, 2014–2019 (OLS)

=====

RESULTS BETA-CONVERGENZA (2014–2019)

=====

OLS Regression Results

=====

Dep. Variable:	g_15_19	R-squared:	0.005
Model:	OLS	Adj. R-squared:	0.001
Method:	Least Squares	F-statistic:	1.149
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	0.285
Time:	18:09:10	Log-Likelihood:	673.90
No. Observations:	236	AIC:	-1344.
Df Residuals:	234	BIC:	-1337.
Df Model:	1		
Covariance Type:	nonrobust		

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0183	0.006	2.873	0.004	0.006	0.031
ln_X0	-0.0011	0.001	-1.072	0.285	-0.003	0.001

=====

Omnibus:	38.231	Durbin-Watson:	1.509
Prob(Omnibus):	0.000	Jarque-Bera (JB):	217.614
Skew:	-0.407	Prob(JB):	5.57e-48
Kurtosis:	7.633	Cond. No.	45.7

Note: OLS estimates of the absolute β -convergence model for the period 2014-2019. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A25. Absolute β -convergence — Structural composition of the economy, 2014–2020 (OLS)

RESULTS BETA-CONVERGENZA (2014-2020)

OLS Regression Results

Dep. Variable:	g_15_20	R-squared:	0.003
Model:	OLS	Adj. R-squared:	-0.001
Method:	Least Squares	F-statistic:	0.8149
Date:	Sat, 11 Apr 2026	Prob (F-statistic):	0.368
Time:	18:09:10	Log-Likelihood:	697.31
No. Observations:	236	AIC:	-1391.
Df Residuals:	234	BIC:	-1384.
Df Model:	1		
Covariance Type:	nonrobust		

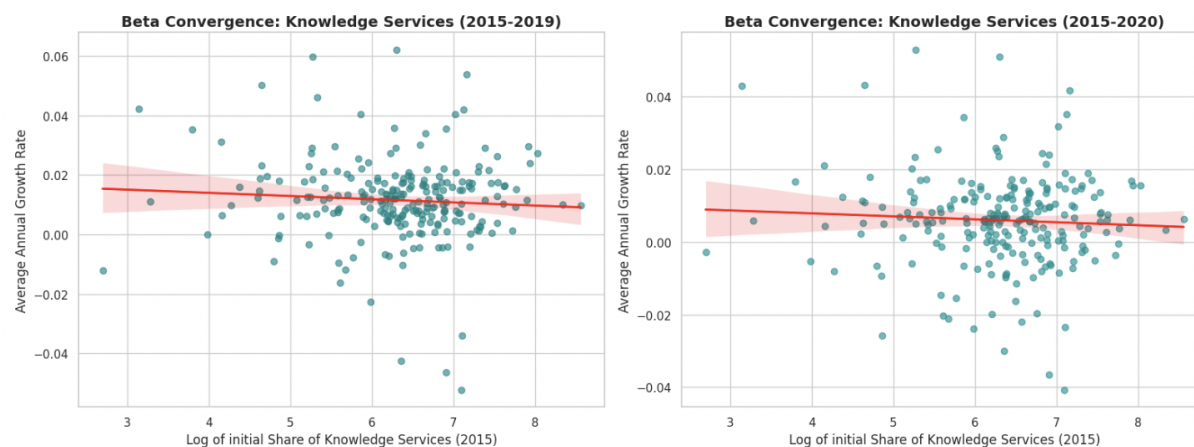
	coef	std err	t	P> t	[0.025	0.975]
const	0.0112	0.006	1.932	0.055	-0.000	0.023
ln_X0	-0.0008	0.001	-0.903	0.368	-0.003	0.001

Omnibus:	18.649	Durbin-Watson:	1.615
Prob(Omnibus):	0.000	Jarque-Bera (JB):	64.458
Skew:	-0.015	Prob(JB):	1.01e-14
Kurtosis:	5.560	Cond. No.	45.7

Note: OLS estimates of the absolute β -convergence model for the period 2014-2020. A negative and statistically significant coefficient on ln_X0 indicates β -convergence. P-values are reported in the corresponding column, and values below 0.05 indicate statistical significance.

Source: Author's elaboration based on Eurostat regional data.

A26. Graph β -convergence — Structural composition of the economy



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level of structural composition of the economy across regions. The fitted line represents the OLS estimate of the absolute β -convergence model. The negative slope indicates convergence.

Source: Author's elaboration based on Eurostat regional data.

APPENDIX B: CONDITIONAL BETA CONVERGENCE RESULTS

This appendix reports the OLS estimates of the conditional β -convergence model, including ERDF per capita as a control variable. The dependent variable is the average annual growth rate, while the explanatory variables are the logarithm of the initial level and the logarithm of ERDF per capita. Results are presented for the periods 2014–2019 and 2014–2020. Scatter plots with fitted regression lines are provided for illustrative purposes.

Figure B1. Conditional β -convergence: GDP per capita (PPS), 2014–2019 and 2014–2020

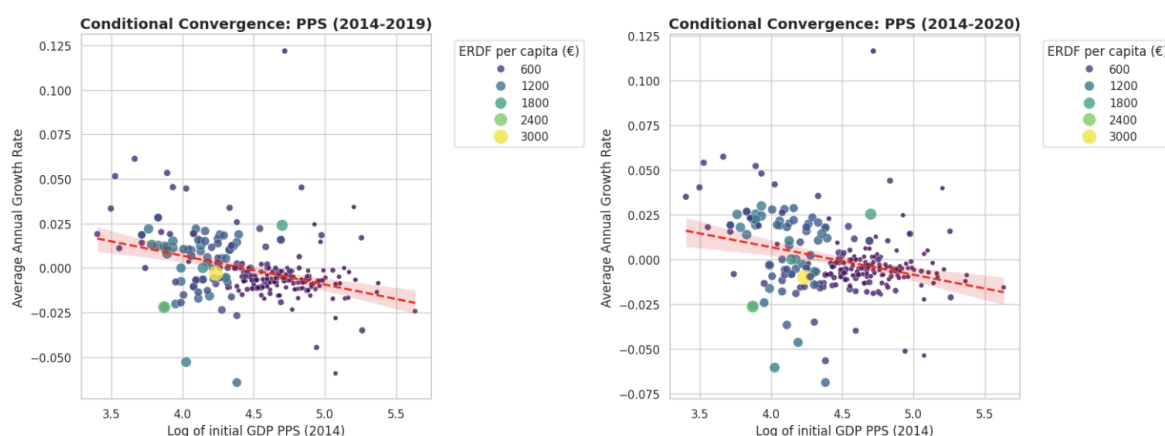
	coef	std err	t	P> t	[0.025	0.975]
const	0.0532	0.022	2.371	0.019	0.009	0.097
ln_X0	-0.0134	0.004	-3.378	0.001	-0.021	-0.006
ln_ERDF	0.0011	0.001	0.978	0.329	-0.001	0.003

	coef	std err	t	P> t	[0.025	0.975]
const	0.0972	0.025	3.910	0.000	0.048	0.146
ln_X0	-0.0198	0.004	-4.506	0.000	-0.028	-0.011
ln_ERDF	-0.0018	0.001	-1.393	0.165	-0.004	0.001

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of GDP per capita (PPS), while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B2. Graph Conditional β -convergence: GDP per capita (PPS), 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B3. Conditional β -convergence: Labour productivity, 2014–2019 and 2014–2020

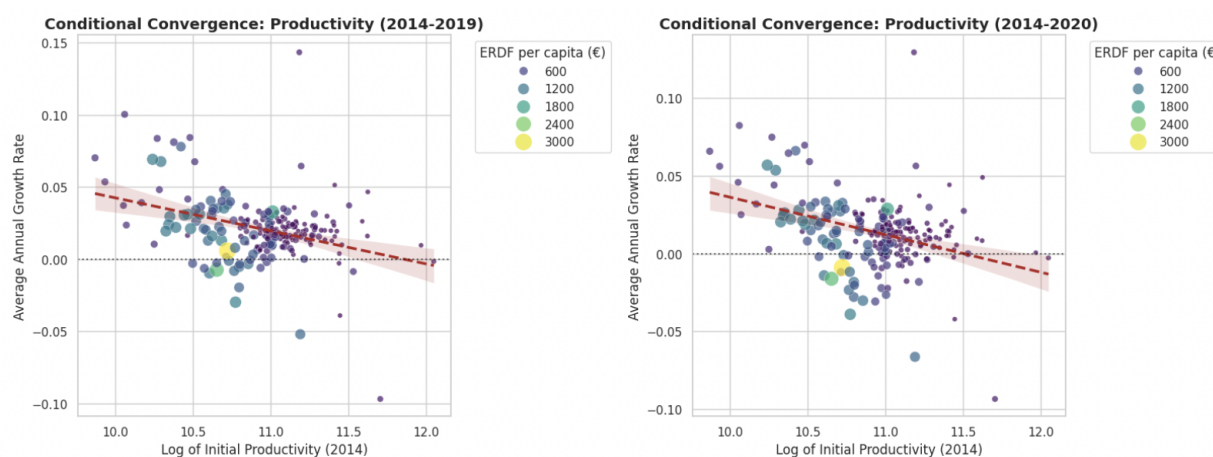
CONDITIONAL BETA-CONVERGENCE: LABOUR PRODUCTIVITY (2014–2019)						
	coef	std err	z	P> z	[0.025	0.975]
const	0.3908	0.087	4.488	0.000	0.220	0.561
ln_X0_prod	-0.0320	0.007	-4.277	0.000	-0.047	-0.017
ln_ERDF	-0.0037	0.001	-2.839	0.005	-0.006	-0.001

CONDITIONAL BETA-CONVERGENCE: LABOUR PRODUCTIVITY (2014–2020)						
	coef	std err	z	P> z	[0.025	0.975]
const	0.4763	0.080	5.990	0.000	0.320	0.632
ln_X0_prod	-0.0393	0.007	-5.765	0.000	-0.053	-0.026
ln_ERDF	-0.0062	0.001	-4.757	0.000	-0.009	-0.004

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of labour productivity, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B4. Conditional β -convergence: Labour productivity, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.

Source: Author's elaboration based on Eurostat regional data.

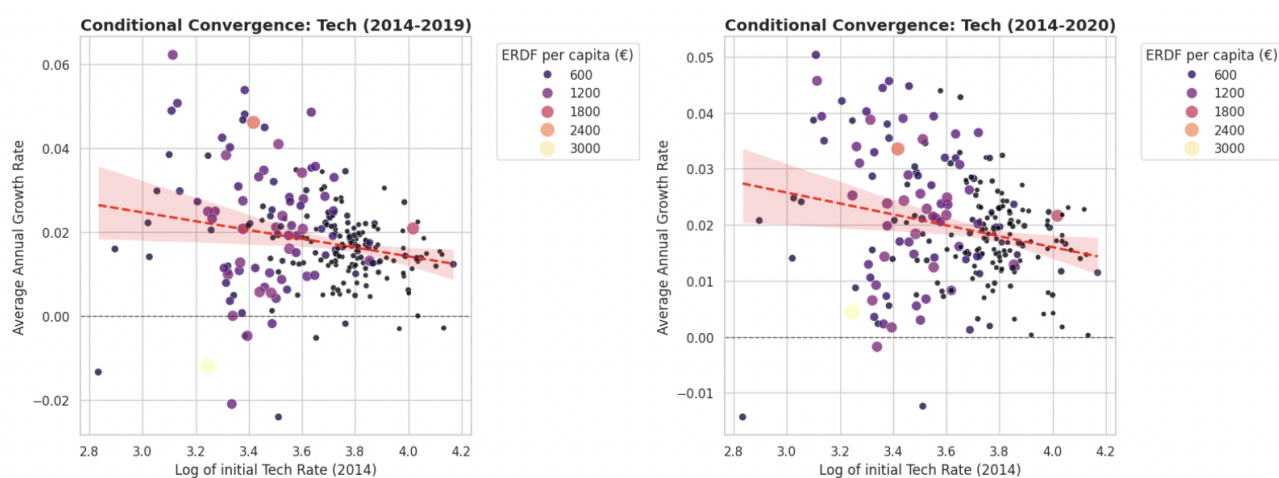
Figure B5. Conditional β -convergence: High-tech employment, 2014–2019 and 2014–2020

--- CONDITIONAL BETA-CONVERGENCE: TECH / HR (2014–2019) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0426	0.021	2.056	0.040	0.002	0.083
ln_X0_tech	-0.0079	0.005	-1.557	0.120	-0.018	0.002
ln_ERDF	0.0008	0.001	1.136	0.256	-0.001	0.002

--- CONDITIONAL BETA-CONVERGENCE: TECH / HR (2014–2020) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0431	0.020	2.167	0.030	0.004	0.082
ln_X0_tech	-0.0075	0.005	-1.547	0.122	-0.017	0.002
ln_ERDF	0.0007	0.001	1.148	0.251	-0.000	0.002

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of high tech and science employment, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.
Source: Author's elaboration based on Eurostat regional data.

Figure B6. Conditional β -convergence: High-tech employment, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.
Source: Author's elaboration based on Eurostat regional data.

Figure B7. Conditional β -convergence: Life expectancy, 2014–2019 and 2014–2020

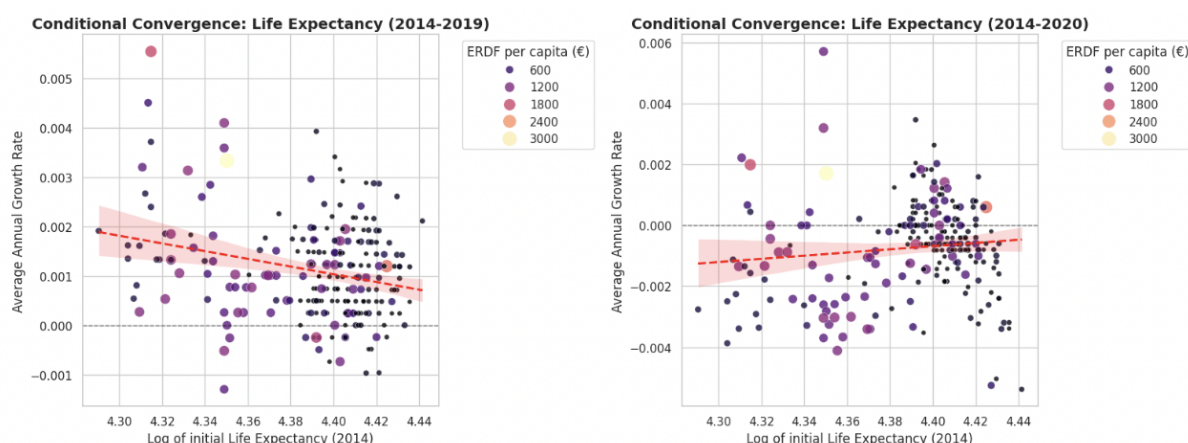
--- CONDITIONAL BETA-CONVERGENCE: LIFE EXPECTANCY (2014–2019) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0330	0.010	3.190	0.001	0.013	0.053
ln_X0_life	-0.0073	0.002	-3.113	0.002	-0.012	-0.003
ln_ERDF	2.702e-05	4.78e-05	0.566	0.572	-6.66e-05	0.000

--- CONDITIONAL BETA-CONVERGENCE: LIFE EXPECTANCY (2014–2020) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	-0.0125	0.018	-0.714	0.475	-0.047	0.022
ln_X0_life	0.0028	0.004	0.716	0.474	-0.005	0.011
ln_ERDF	-0.0001	8.09e-05	-1.588	0.112	-0.000	3.01e-05

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of life expectancy, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B8. Conditional β -convergence: Life expectancy, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence. The positive slope indicates divergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B9. Conditional β -convergence: Tertiary education attainment, 2014–2019 and 2014–2020

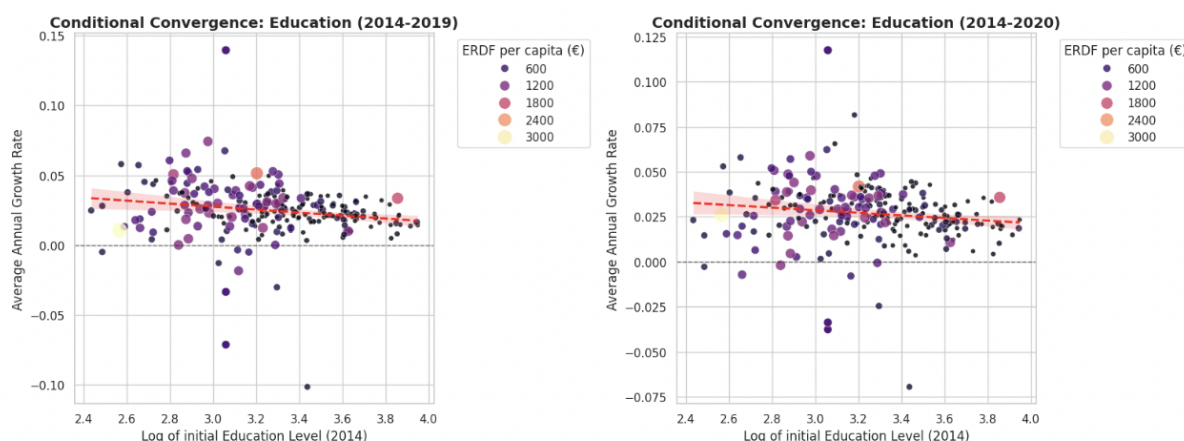
--- CONDITIONAL BETA-CONVERGENCE: EDUCATION (2014–2019) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0609	0.013	4.673	0.000	0.035	0.086
ln_X0_edu	-0.0109	0.003	-3.180	0.001	-0.018	-0.004
ln_ERDF	-0.0001	0.001	-0.135	0.892	-0.002	0.002

--- CONDITIONAL BETA-CONVERGENCE: EDUCATION (2014–2020) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0590	0.012	5.016	0.000	0.036	0.082
ln_X0_edu	-0.0086	0.003	-2.756	0.006	-0.015	-0.002
ln_ERDF	-0.0008	0.001	-0.983	0.326	-0.002	0.001

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of tertiary education attainment, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B10. Conditional β -convergence: Tertiary education attainment, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B11. Conditional β -convergence: NEET rate, 2014–2019 and 2014–2020

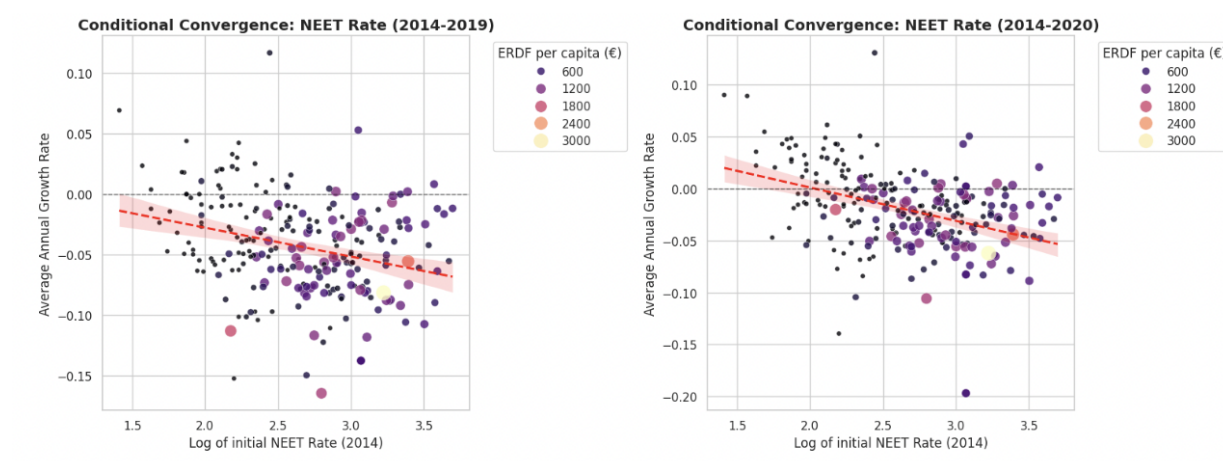
--- CONDITIONAL BETA-CONVERGENCE: NEET RATE (2014–2019) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0219	0.014	1.531	0.126	-0.006	0.050
ln_X0_neet	-0.0145	0.006	-2.272	0.023	-0.027	-0.002
ln_ERDF	-0.0051	0.002	-2.237	0.025	-0.010	-0.001

--- CONDITIONAL BETA-CONVERGENCE: NEET RATE (2014–2020) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0666	0.014	4.689	0.000	0.039	0.094
ln_X0_neet	-0.0254	0.006	-4.556	0.000	-0.036	-0.014
ln_ERDF	-0.0036	0.002	-1.805	0.071	-0.008	0.000

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of NEET rate, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B12. Conditional β -convergence: NEET rate, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.

Source: Author's elaboration based on Eurostat regional data.

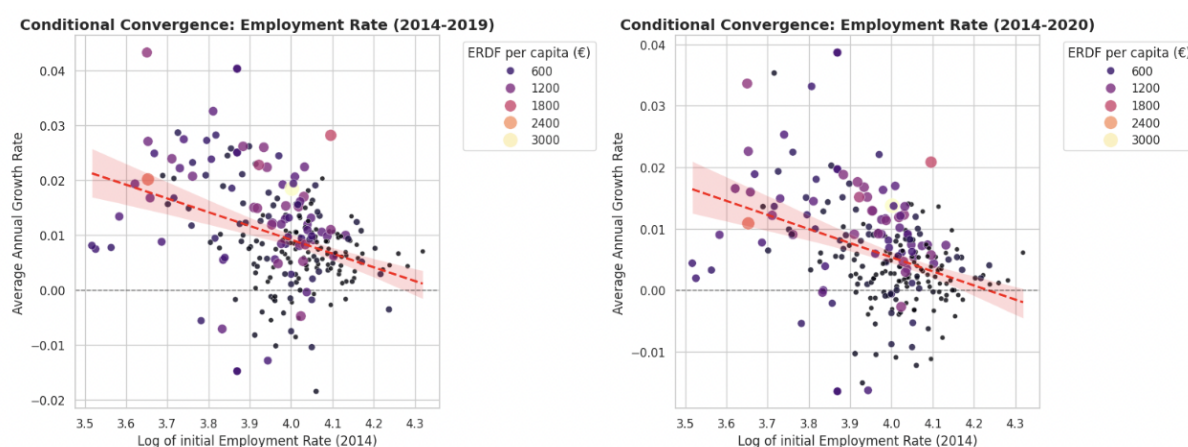
Figure B13. Conditional β -convergence: Employment rate, 2014–2019 and 2014–2020

--- CONDITIONAL BETA-CONVERGENCE: EMPLOYMENT RATE (2014–2019) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0670	0.018	3.630	0.000	0.031	0.103
ln_X0_empl	-0.0167	0.004	-3.785	0.000	-0.025	-0.008
ln_ERDF	0.0018	0.000	4.641	0.000	0.001	0.003
--- CONDITIONAL BETA-CONVERGENCE: EMPLOYMENT RATE (2014–2020) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0544	0.018	3.099	0.002	0.020	0.089
ln_X0_empl	-0.0145	0.004	-3.449	0.001	-0.023	-0.006
ln_ERDF	0.0018	0.000	5.419	0.000	0.001	0.002

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of employment rate, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B14. Conditional β -convergence: Employment rate, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.

Source: Author's elaboration based on Eurostat regional data.

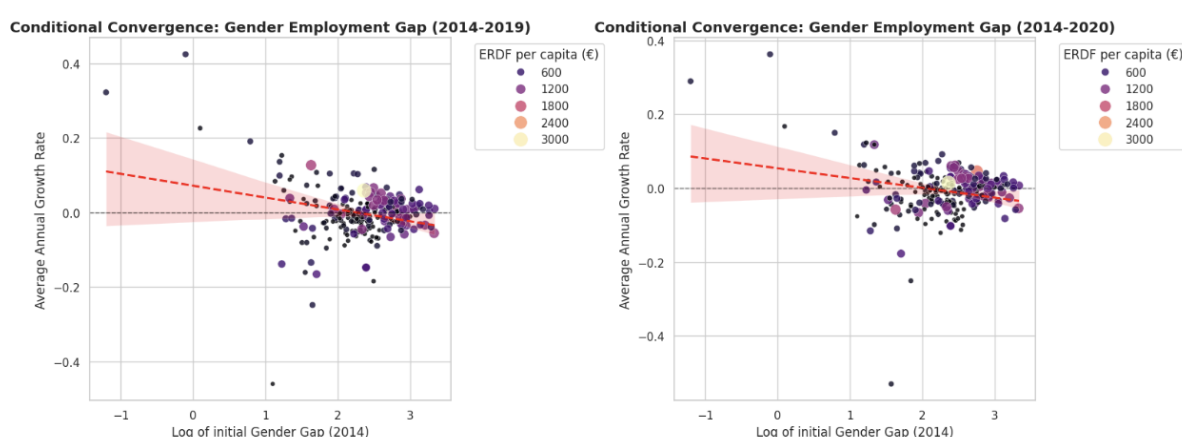
Figure B15. Conditional β -convergence: Gender employment gap, 2014–2019 and 2014–2020

--- CONDITIONAL BETA-CONVERGENCE: GENDER GAP (2014–2019) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0136	0.041	0.333	0.739	-0.067	0.094
ln_X0_gender	-0.0413	0.018	-2.274	0.023	-0.077	-0.006
ln_ERDF	0.0152	0.004	3.673	0.000	0.007	0.023
--- CONDITIONAL BETA-CONVERGENCE: GENDER GAP (2014–2020) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0105	0.030	0.348	0.728	-0.049	0.070
ln_X0_gender	-0.0335	0.017	-2.020	0.043	-0.066	-0.001
ln_ERDF	0.0114	0.003	3.587	0.000	0.005	0.018

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of gender employment gap, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B16. Conditional β -convergence: Gender employment gap, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B17. Conditional β -convergence: structural composition of the economy, 2014–2019 and 2014–2020

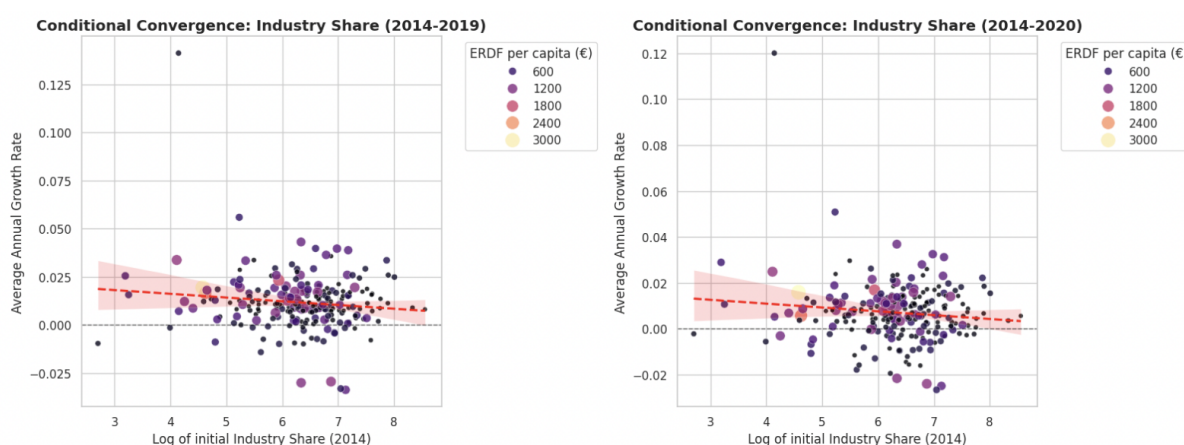
--- CONDITIONAL BETA-CONVERGENCE: INDUSTRY SHARE (2014–2019) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0226	0.014	1.564	0.118	-0.006	0.051
ln_X0_sector	-0.0019	0.002	-0.989	0.323	-0.006	0.002
ln_ERDF	0.0002	0.001	0.273	0.785	-0.001	0.001

--- CONDITIONAL BETA-CONVERGENCE: INDUSTRY SHARE (2014–2020) ---						
	coef	std err	z	P> z	[0.025	0.975]
const	0.0181	0.012	1.467	0.142	-0.006	0.042
ln_X0_sector	-0.0017	0.002	-1.048	0.294	-0.005	0.001
ln_ERDF	-6.089e-05	0.001	-0.105	0.916	-0.001	0.001

Notes: OLS estimates of the conditional β -convergence model. ln_X0 denotes the logarithm of the initial level of structural composition of the economy, while ln_ERDF denotes the logarithm of ERDF per capita. P-values are reported in the corresponding column; values below 0.05 indicate statistical significance. A negative and statistically significant coefficient on ln_X0 indicates conditional β -convergence.

Source: Author's elaboration based on Eurostat regional data.

Figure B18. Conditional β -convergence: Sector employment, 2014–2019 and 2014–2020



Notes: The figure shows the relationship between the average annual growth rate and the logarithm of the initial level across regions. The fitted line represents the OLS estimate. The colour and size of points reflect ERDF per capita. A negative slope indicates β -convergence.

Source: Author's elaboration based on Eurostat regional data.

APPENDIX C: SPATIAL DURBIN RESULTS

This appendix reports the estimates of the Spatial Durbin Model (SDM) for the indicators considered in the analysis. The model accounts for spatial dependence by including both the spatial lag of the dependent variable and the spatially lagged explanatory variables. Results are presented for the periods 2014–2019 and 2014–2020. Scatter plots are provided for illustrative purposes.

Figure C1. Spatial Durbin model: GDP per capita (PPS), 2014–2019

```

--- Spatial Durbin Model: Queen Contiguity (2014–2019) ---
ML_Lag
REGRESSION RESULTS
-----

SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)
-----
Data set      :      unknown
Weights matrix :      Queen
Dependent Variable : Growth_14_19
Mean dependent var :      0.0000
S.D. dependent var :      0.0180
Pseudo R-squared :      0.4403
Spatial Pseudo R-squared: 0.2185
Log likelihood :    621.8334
Sigma-square ML :      0.0002
S.E of regression :      0.0136

Number of Observations:      219
Number of Variables :      4
Degrees of Freedom :      215

Akaike info criterion : -1235.667
Schwarz criterion : -1222.111
-----

Variable      Coefficient      Std.Error      z-Statistic      Probability
-----
CONSTANT      0.03018      0.01846      1.63488      0.10207
ln_X0      -0.00771      0.00327      -2.35706      0.01842
ln_ERDF      0.00086      0.00098      0.87709      0.38044
W_Growth_14_19      0.54853      0.06203      8.84357      0.00000
-----

SPATIAL LAG MODEL IMPACTS
Impacts computed using the 'simple' method.
Variable      Direct      Indirect      Total
ln_X0      -0.0077      -0.0094      -0.0171
ln_ERDF      0.0009      0.0010      0.0019
===== END OF REPORT =====

```

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of GDP per capita (PPS), capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C2. Spatial Durbin model: Labour productivity, 2014–2019

=====				
SPATIAL DURBIN MODEL (SAR): LABOUR PRODUCTIVITY (2014–2019)				
=====				
ML_Lag				
REGRESSION RESULTS				
=====				
SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)				

Data set	:	unknown		
Weights matrix	:	Queen		
Dependent Variable	:	Growth_Prod_14_19	Number of Observations:	213
Mean dependent var	:	0.0222	Number of Variables	4
S.D. dependent var	:	0.0197	Degrees of Freedom	209
Pseudo R-squared	:	0.3926		
Spatial Pseudo R-squared	:	0.1722		
Log likelihood	:	578.1669		
Sigma-square ML	:	0.0002	Akaike info criterion	-1148.334
S.E of regression	:	0.0154	Schwarz criterion	-1134.889

Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	0.22428	0.04845	4.62871	0.00000
ln_X0_prod	-0.01863	0.00409	-4.55471	0.00001
ln_ERDF	-0.00190	0.00100	-1.89053	0.05869
W_Growth_Prod_14_19	0.51507	0.06339	8.12547	0.00000

SPATIAL LAG MODEL IMPACTS				
Impacts computed using the 'simple' method.				
Variable	Direct	Indirect	Total	
ln_X0_prod	-0.0186	-0.0198	-0.0384	
ln_ERDF	-0.0019	-0.0020	-0.0039	
===== END OF REPORT =====				

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of labour productivity, capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C3. Spatial Durbin model: High-tech employment, 2014–2019

=====				
SPATIAL LAG MODEL: HIGH-TECH EMPLOYMENT (2014–2019)				
=====				
ML_Lag				
REGRESSION RESULTS				
=====				
SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)				

Data set	:	unknown		
Weights matrix	:	Queen		
Dependent Variable	:	Growth_Tech_14_19	Number of Observations:	213
Mean dependent var	:	0.0173	Number of Variables	4
S.D. dependent var	:	0.0110	Degrees of Freedom	209
Pseudo R-squared	:	0.0434		
Spatial Pseudo R-squared	:	0.0405		
Log likelihood	:	664.4028		
Sigma-square ML	:	0.0001	Akaike info criterion	-1320.806
S.E of regression	:	0.0107	Schwarz criterion	-1307.360

Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	0.03267	0.01617	2.02115	0.04326
ln_X0_tech	-0.00557	0.00377	-1.47578	0.14000
ln_ERDF	0.00083	0.00067	1.23807	0.21569
W_Growth_Tech_14_19	0.04586	0.09157	0.50083	0.61649

SPATIAL LAG MODEL IMPACTS				
Impacts computed using the 'simple' method.				
Variable	Direct	Indirect	Total	
ln_X0_tech	-0.0056	-0.0003	-0.0058	
ln_ERDF	0.0008	0.0000	0.0009	
===== END OF REPORT =====				

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of high tech employment, capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C4. Spatial Durbin model: Life expectancy, 2014–2019

SPATIAL LAG MODEL: LIFE EXPECTANCY (2014–2019)				
ML_Lag REGRESSION RESULTS				
SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)				
Data set	:	unknown		
Weights matrix	:	Queen		
Dependent Variable	:	Growth_Life_14_19	Number of Observations:	213
Mean dependent var	:	0.0011	Number of Variables	4
S.D. dependent var	:	0.0010	Degrees of Freedom	209
Pseudo R-squared	:	0.4717		
Spatial Pseudo R-squared	:	0.0619		
Log likelihood	:	1220.4920		
Sigma-square ML	:	0.0000	Akaike info criterion	-2432.984
S.E of regression	:	0.0007	Schwarz criterion	-2419.539
Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	0.01607	0.00788	2.04010	0.04134
ln_X0_life	-0.00355	0.00177	-2.00813	0.04463
ln_ERDF	-0.00002	0.00004	-0.48072	0.63071
W_Growth_Life_14_19	0.63737	0.05565	11.45387	0.00000
SPATIAL LAG MODEL IMPACTS				
Impacts computed using the 'simple' method.				
Variable	Direct	Indirect	Total	
ln_X0_life	-0.0035	-0.0062	-0.0098	
ln_ERDF	-0.0000	-0.0000	-0.0001	
END OF REPORT				

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of life expectancy, capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C5. Spatial Durbin model: Tertiary education attainment, 2014–2019

```
=====
SPATIAL LAG MODEL: EDUCATION (2014–2019)
=====
ML_Lag
REGRESSION RESULTS
=====

SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)
=====
Data set      : unknown
Weights matrix : Queen
Dependent Variable : Growth_Edu_14_19
Mean dependent var : 0.0244
S.D. dependent var : 0.0200
Pseudo R-squared : 0.0672
Spatial Pseudo R-squared: 0.0100
Log likelihood : 550.8723
Sigma-square ML : 0.0004
S.E of regression : 0.0194

Number of Observations: 219
Number of Variables : 4
Degrees of Freedom : 215

Akaike info criterion : -1093.745
Schwarz criterion : -1080.188

=====
Variable      Coefficient      Std.Error      z-Statistic      Probability
=====
CONSTANT      0.04340          0.01802        2.40848          0.01602
ln_X0_edu     -0.00757          0.00455        -1.66234          0.09644
ln_ERDF       -0.00005          0.00105        -0.04866          0.96119
W_Growth_Edu_14_19 0.25151          0.08360        3.00846          0.00263
=====

SPATIAL LAG MODEL IMPACTS
Impacts computed using the 'simple' method.
Variable      Direct      Indirect      Total
ln_X0_edu     -0.0076     -0.0025      -0.0101
ln_ERDF       -0.0001     -0.0000      -0.0001
=====
END OF REPORT
=====
```

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of tertiary education attainment, capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C6. Spatial Durbin model: NEET rate, 2014–2019

```
=====
SPATIAL LAG MODEL: NEET RATE (2014–2019)
=====
ML_Lag
REGRESSION RESULTS
=====

SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)
=====
Data set      : unknown
Weights matrix : Queen
Dependent Variable : Growth_NEET_14_19
Mean dependent var : -0.0440
S.D. dependent var : 0.0384
Pseudo R-squared : 0.3311
Spatial Pseudo R-squared: 0.1597
Log likelihood : 439.8522
Sigma-square ML : 0.0010
S.E of regression : 0.0315

Number of Observations: 219
Number of Variables : 4
Degrees of Freedom : 215

Akaike info criterion : -871.704
Schwarz criterion : -858.148

=====
Variable      Coefficient      Std.Error      z-Statistic      Probability
=====
CONSTANT      0.02218          0.01226        1.80877          0.07049
ln_X0_neet    -0.01134          0.00595        -1.90405          0.05690
ln_ERDF       -0.00316          0.00203        -1.55505          0.11993
W_Growth_NEET_14_19 0.46788          0.06926        6.75533          0.00000
=====

SPATIAL LAG MODEL IMPACTS
Impacts computed using the 'simple' method.
Variable      Direct      Indirect      Total
ln_X0_neet    -0.0113     -0.0100      -0.0213
ln_ERDF       -0.0032     -0.0028      -0.0059
=====
END OF REPORT
=====
```

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of the NEET rate, capturing spillover effects across neighbouring regions. The SDM allows the

decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C7. Spatial Durbin model: Employment rate, 2014–2019

SPATIAL LAG MODEL: EMPLOYMENT RATE (2014–2019)				
ML_Lag REGRESSION RESULTS				
SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)				
Data set	:	unknown		
Weights matrix	:	Queen		
Dependent Variable	:	Growth_EMPL_14_19	Number of Observations:	219
Mean dependent var	:	0.0093	Number of Variables	4
S.D. dependent var	:	0.0086	Degrees of Freedom	215
Pseudo R-squared	:	0.4649		
Spatial Pseudo R-squared	:	0.2065		
Log likelihood	:	786.2087		
Sigma-square ML	:	0.0000	Akaike info criterion	-1564.417
S.E of regression	:	0.0064	Schwarz criterion	-1550.861
Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	0.03614	0.01590	2.27243	0.02306
ln_X0_empl	-0.00911	0.00376	-2.42496	0.01531
ln_ERDF	0.00082	0.00037	2.24343	0.02487
W_Growth_EMPL_14_19	0.57237	0.06009	9.52538	0.00000
SPATIAL LAG MODEL IMPACTS				
Impacts computed using the 'simple' method.				
Variable	Direct	Indirect	Total	
ln_X0_empl	-0.0091	-0.0122	-0.0213	
ln_ERDF	0.0008	0.0011	0.0019	
===== END OF REPORT =====				

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of the employment rate, capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C8. Spatial Durbin model: Gender employment gap, 2014–2019

=====				
SPATIAL LAG MODEL: GENDER GAP (2014–2019)				
=====				
ML_Lag				
REGRESSION RESULTS				
=====				
SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)				

Data set	:	unknown		
Weights matrix	:	Queen		
Dependent Variable	:	Growth_Gender_14_19	Number of Observations:	218
Mean dependent var	:	-0.0029	Number of Variables	4
S.D. dependent var	:	0.0726	Degrees of Freedom	214
Pseudo R-squared	:	0.1397		
Spatial Pseudo R-squared	:	0.1405		
Log likelihood	:	279.2031		
Sigma-square ML	:	0.0045	Akaike info criterion	-550.406
S.E of regression	:	0.0672	Schwarz criterion	-536.868

Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	0.00857	0.02267	0.37804	0.70540
ln_X0_gender	-0.04068	0.00850	-4.78619	0.00000
ln_ERDF	0.01589	0.00362	4.39530	0.00001
W_Growth_Gender_14_19	-0.00795	0.09001	-0.08830	0.92964

SPATIAL LAG MODEL IMPACTS				
Impacts computed using the 'simple' method.				
Variable	Direct	Indirect	Total	
ln_X0_gender	-0.0407	0.0003	-0.0404	
ln_ERDF	0.0159	-0.0001	0.0158	
===== END OF REPORT =====				

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of the gender employment gap capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

Figure C9. Spatial Durbin model: Structural composition of the economy, 2014–2019

=====				
SPATIAL LAG MODEL: INDUSTRY SHARE (2014–2019)				
=====				
ML_Lag				
REGRESSION RESULTS				
=====				
SUMMARY OF OUTPUT: MAXIMUM LIKELIHOOD SPATIAL LAG (METHOD = FULL)				

Data set	:	unknown		
Weights matrix	:	Queen		
Dependent Variable	:	Growth_Sector_14_19	Number of Observations:	213
Mean dependent var	:	0.0105	Number of Variables	4
S.D. dependent var	:	0.0111	Degrees of Freedom	209
Pseudo R-squared	:	0.2598		
Spatial Pseudo R-squared	:	0.0003		
Log likelihood	:	677.7374		
Sigma-square ML	:	0.0001	Akaike info criterion	-1347.475
S.E of regression	:	0.0097	Schwarz criterion	-1334.030

Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	-0.00017	0.00670	-0.02526	0.97985
ln_X0_sector	0.00072	0.00090	0.80518	0.42072
ln_ERDF	0.00023	0.00050	0.45500	0.64911
W_Growth_Sector_14_19	0.48635	0.06944	7.00438	0.00000

SPATIAL LAG MODEL IMPACTS				
Impacts computed using the 'simple' method.				
Variable	Direct	Indirect	Total	
ln_X0_sector	0.0007	0.0007	0.0014	
ln_ERDF	0.0002	0.0002	0.0004	
===== END OF REPORT =====				

Note: Estimates are based on the Spatial Durbin Model (SDM). W_Growth_Sector denotes the spatial lag of the dependent variable, capturing spillover effects across neighbouring regions. The SDM allows the decomposition of impacts into direct effects, measuring the effect within the same region, and indirect effects, capturing spillovers on neighbouring regions.

Source: Author's elaboration based on Eurostat regional data.

APPENDIX D: VARIABLES AND DATA SOURCES

This table summarises all indicators and variables used in the empirical analysis, organised by analytical category. The analysis covers 244 NUTS 2 regions across 27 EU Member States for the 2014–2020 programming period.

Variable	Code	Definition	Categories	Source & Dataset
GDP per capita in Purchasing Power Standards	GDP_PPS	Average economic output per inhabitant, expressed in PPS to eliminate price-level differences across countries. Standard benchmark for regional economic prosperity and convergence.	PPS (index or absolute value)	Eurostat – Regional Economic Accounts
Labour Productivity	PROD	Efficiency of production inputs, measured as the ratio between Gross Value Added (GVA) and the number of employees. Captures structural economic efficiency and long-term competitiveness.	GVA / number of employees	Eurostat – Regional Economic Accounts / National Accounts
Employment in High-Technology and Science Sectors	TECH	Number of people employed in human resources in science and technology (HRST) sectors. Used as a proxy for regional technological capacity and innovation potential.	Number of persons (thousands)	Eurostat – Regional Statistics (HRST)
Life Expectancy at Birth	LIFE	Average number of years a newborn could expect to live if exposed to current age-specific death rates. Proxy for population health, quality of healthcare systems and overall living conditions.	Years	Eurostat – Regional Demographic Statistics
Tertiary Educational Attainment	EDU	Share of the population aged 25–64 holding a tertiary education degree (ISCED 5–8). Indicator of human capital stock and long-term socioeconomic convergence potential.	% of population aged 25–64	Eurostat – Regional Labour Force Survey (LFS)
NEET Rate	NEET	Percentage of the population aged 18–24 not in education, employment or training. Captures acute social and economic vulnerability among youth and is an EU 2030 social target.	% of population aged 18–24	Eurostat – Regional Labour Force Survey (LFS)
Employment Rate	EMP	Proportion of employed individuals as a percentage of the total working-age population. Key indicator for assessing regional labour market performance and EU 2030 employment targets.	% of working-age population	Eurostat – Regional Labour Force Survey (LFS)
Gender Employment Gap	GEN	Difference between the employment rates of men and women aged 15–64. Captures structural labour market inequality and is used to assess the gender-neutrality of ERDF funding.	Percentage points (male rate minus female rate)	Eurostat – Regional Labour Force Survey (LFS)
Employment by Economic Activity (Sectoral Share)	ACT	Distribution of employment across economic sectors, used here as a measure of employment in knowledge-intensive services. Captures structural composition and sectoral transformation of regional labour markets.	Number of persons / sector share (%)	Eurostat – Regional Labour Force Survey (LFS)

ERDF Payments per Capita	ERDF	Total cumulative ERDF allocations to each NUTS2 region over 2014–2020, normalised by the region's initial population (2014) to capture funding intensity rather than absolute amount.	EUR per capita (cumulative 2014–2020)	ESPON Database – "Historic EU Payments – Annual Timeseries, Regionalised and Modelled"
Regional Population	POP	Annual population figures at the NUTS 2 level, used as a denominator to compute per capita ERDF funding intensity and to ensure regional comparability.	Number of persons	Eurostat – Regional Demographic Statistics
Institutional Depth (Decentralisation)	instdepth	Level of decentralisation measuring the degree of political, fiscal and administrative autonomy of regional governments. Classified on a 4-point ordinal scale: (0) no regional administration, (1) deconcentrated, (2) non-deconcentrated subject to central veto, (3) non-deconcentrated not subject to veto.	Ordinal scale 0–3	Regional Authority Index (RAI) – Hooghe, Marks & Schakel (2016); updated dataset covering 95 countries 1950–2018
Political Orientation of National Government	gov_paty	Cabinet composition by political colour, assigned on a 5-point scale: (1) hegemony of right/centre parties, (2) dominance of right/centre parties, (3) balance between left and right, (4) dominance of social-democratic/left parties, (5) hegemony of social-democratic/left parties.	Ordinal scale 1–5	Comparative Political Data Set 1960–2023 – Armingeon, Engler, Leemann & Weisstanner (2025); annual data for 36 OECD and EU countries
Openness of the Economy	openc	Total trade (sum of imports and exports) as a percentage of GDP at current prices. Used as a proxy for economic integration and exposure to international market forces. Recoded into 5 ordinal categories from closed (0) to highly open (4).	Ordinal scale 0–4 (derived from % of GDP)	Comparative Political Data Set 1960–2023 – Armingeon, Engler, Leemann & Weisstanner (2025); annual data for 36 OECD and EU countries
Quality of Government Score	equi-score_nuts0	Composite index measuring sub-national governance quality based on four dimensions: rule of law, control of corruption, bureaucratic effectiveness, and strength of electoral institutions. Based on a 34-question survey with over 34,000 respondents. Divided into 4 ordinal clusters in the analysis.	Ordinal scale (4 clusters, low to high quality)	Quality of Government (QoG) EU Regional Dataset – University of Gothenburg, Quality of Government Institute

Notes: All regional indicators are measured at the NUTS 2 level according to the 2021 Eurostat nomenclature for N=244. Institutional and political control variables are measured at the national (NUTS 0) level due to data availability constraints. ERDF funding data covers the 2014–2020 programming period only.

APPENDIX E: LIST OF LAGGING REGIONS

This appendix reports the full list of regions identified as “lagging” or “trapped” according to the β -convergence analysis. A region is classified as trapped when it does not exhibit convergence dynamics in one or more indicators over the period considered. The table summarises, for each region, the presence of divergence or lack of convergence across all indicators. The total number of traps provides a synthetic measure of structural weakness.

Region	GDP	Prod	Tech	Life	Edu	NEET	Empl	Gender	Sector	Total
DE80	0	0	1	1	1	1	1	1	1	7
DEG0	1	0	1	1	1	1	0	1	0	6
FRF3	1	1	1	0	0	1	1	1	0	6
ITF6	1	1	1	0	1	0	1	0	1	6
BE34	1	1	1	1	0	1	0	0	0	5
BG34	0	1	1	0	1	0	0	1	1	5
DE40	1	1	1	0	0	1	0	1	0	5
DED4	1	0	1	0	1	0	0	1	1	5
DEE0	1	0	0	1	1	1	0	1	0	5
DEF0	0	1	1	0	1	1	0	1	0	5
FRD2	1	0	1	0	0	0	1	1	1	5
FRE2	1	1	0	0	0	0	1	1	1	5
FRI3	1	0	1	0	0	0	1	1	1	5
FRK1	1	0	1	0	0	1	1	0	1	5
FRY2	1	0	0	0	1	0	1	1	1	5
FRY4	1	0	1	0	0	0	1	1	1	5
ITI2	1	1	0	0	1	0	1	0	1	5
BE22	0	0	0	0	0	1	1	1	1	4
BE32	1	1	0	0	0	0	0	1	1	4
BE35	1	0	0	0	0	0	1	1	1	4
DE22	0	0	1	0	1	0	0	1	1	4
DE24	0	0	1	0	1	0	0	1	1	4
DE93	1	0	1	0	1	0	0	1	0	4
EL63	1	1	0	0	1	0	0	0	1	4
FI1C	0	0	0	0	0	1	1	1	1	4
FI1D	1	1	0	0	0	0	1	0	1	4
FRF2	1	0	1	0	0	0	1	0	1	4
HU22	1	1	0	0	1	1	0	0	0	4
ITF4	1	1	1	0	1	0	0	0	0	4
ITG1	1	0	1	0	1	0	1	0	0	4
ITI3	1	0	1	0	0	0	1	0	1	4
NL12	0	1	0	0	0	1	0	1	1	4
NL13	0	1	1	0	0	1	0	0	1	4
PL41	0	1	1	1	0	1	0	0	0	4
PL72	0	0	1	1	0	0	1	0	1	4
SE31	0	1	1	0	0	0	0	1	1	4
AT31	0	0	0	0	0	1	0	1	1	3
AT33	0	0	0	0	1	0	0	1	1	3

AT34	0	0	1	0	1	0	0	1	0	3
BE24	0	0	0	0	0	1	0	1	1	3
BE31	0	0	0	0	0	1	0	1	1	3
BE33	1	0	0	0	0	0	0	1	1	3
BG31	0	0	1	0	1	0	0	0	1	3
CZ02	0	0	0	1	1	1	0	0	0	3
CZ04	0	0	1	0	1	0	0	0	1	3
CZ05	0	0	0	1	1	0	0	0	1	3
CZ06	0	0	0	1	1	1	0	0	0	3
CZ07	0	0	0	1	1	0	0	0	1	3
DE73	0	0	1	0	0	0	0	1	1	3
DE91	0	0	0	0	0	1	0	1	1	3
DE92	0	0	1	0	1	0	0	1	0	3
DE94	0	0	1	0	1	0	0	1	0	3
DEA1	0	0	1	1	1	0	0	0	0	3
DEA3	0	1	0	0	1	0	0	1	0	3
DEA5	0	0	1	1	1	0	0	0	0	3
DEB2	0	1	0	0	0	0	0	1	1	3
DEC0	0	0	1	1	0	0	0	0	1	3
DED5	0	1	0	0	0	1	0	1	0	3
DK05	0	0	1	0	0	0	0	1	1	3
EE00	0	0	0	0	0	1	0	1	1	3
EL41	1	1	0	0	1	0	0	0	0	3
EL43	1	1	1	0	0	0	0	0	0	3
EL65	1	1	1	0	0	0	0	0	0	3
ES13	1	1	1	0	0	0	0	0	0	3
ES42	0	1	1	0	1	0	0	0	0	3
ES43	0	1	1	0	1	0	0	0	0	3
ES63	1	0	0	0	1	0	1	0	0	3
ES70	1	1	1	0	0	0	0	0	0	3
FRC1	1	0	0	0	0	0	1	0	1	3
FRC2	1	0	0	0	0	0	1	0	1	3
FRD1	1	0	0	0	0	0	1	0	1	3
FRE1	1	0	0	0	0	0	1	1	0	3
FRI2	1	0	0	0	0	0	1	0	1	3
FRJ1	1	0	0	0	0	0	1	1	0	3
FRY1	1	0	0	0	0	0	1	0	1	3
FRY3	1	0	0	0	0	0	1	0	1	3
HR03	0	0	1	0	0	0	1	0	1	3
HU12	0	1	0	0	1	1	0	0	0	3
HU32	0	1	0	1	1	0	0	0	0	3
ITC2	0	0	0	0	0	0	1	1	1	3
ITF1	1	0	0	0	0	0	1	0	1	3
ITF3	1	0	0	0	1	0	1	0	0	3
ITF5	0	0	0	0	1	0	1	0	1	3
ITG2	1	1	0	0	0	0	0	0	1	3

LV00	0	0	1	0	0	1	0	1	0	3
NL11	0	0	0	0	0	1	0	1	1	3
NL34	0	1	0	0	0	1	0	0	1	3
PL51	0	1	0	1	0	1	0	0	0	3
PL61	0	1	0	1	0	0	1	0	0	3
PL63	0	1	0	1	0	1	0	0	0	3
PL84	0	0	1	1	0	1	0	0	0	3
PT11	0	1	0	0	0	1	0	1	0	3
PT20	1	1	0	0	1	0	0	0	0	3
RO21	0	0	0	1	1	1	0	0	0	3
SE32	0	0	1	0	0	0	0	1	1	3
SI03	0	0	0	1	0	1	0	1	0	3
SK03	1	1	0	1	0	0	0	0	0	3
AT11	1	0	0	0	0	0	0	0	1	2
BE23	0	0	0	0	0	0	0	1	1	2
BE25	0	0	0	0	0	1	0	0	1	2
BG33	0	0	0	0	1	0	0	0	1	2
BG42	0	0	0	0	1	0	0	0	1	2
CZ03	0	0	0	1	0	0	0	0	1	2
CZ08	0	0	0	1	0	0	0	0	1	2
DE23	0	0	0	0	1	0	0	0	1	2
DE26	0	0	0	0	1	0	0	0	1	2
DE27	0	0	0	0	1	0	0	1	0	2
DE71	0	0	0	0	0	1	0	1	0	2
DE72	0	0	0	0	1	0	0	0	1	2
DEA4	0	0	1	0	1	0	0	0	0	2
DEB1	0	1	0	0	0	0	0	0	1	2
DEB3	0	0	0	0	1	0	0	1	0	2
DED2	0	0	0	0	0	1	0	0	1	2
DK03	0	0	1	0	0	0	0	1	0	2
EL42	1	1	0	0	0	0	0	0	0	2
EL51	1	1	0	0	0	0	0	0	0	2
EL52	1	1	0	0	0	0	0	0	0	2
EL53	1	0	0	0	0	0	0	0	1	2
EL54	1	1	0	0	0	0	0	0	0	2
EL61	1	1	0	0	0	0	0	0	0	2
EL62	1	1	0	0	0	0	0	0	0	2
EL64	1	1	0	0	0	0	0	0	0	2
ES12	0	0	0	0	0	0	0	1	1	2
ES21	0	0	0	0	0	1	0	1	0	2
ES30	0	0	0	0	0	1	0	1	0	2
ES62	0	1	1	0	0	0	0	0	0	2
FI20	0	0	0	0	0	0	0	1	1	2
FRB0	1	0	0	0	0	0	1	0	0	2
FRG0	1	0	0	0	0	0	0	1	0	2
FRH0	1	0	0	0	0	0	0	1	0	2

FRI1	0	0	0	0	0	0	1	1	0	2
FRL0	0	0	0	0	0	0	1	1	0	2
FRM0	1	0	0	0	1	0	0	0	0	2
HU11	0	0	0	1	0	1	0	0	0	2
HU21	0	0	0	1	0	1	0	0	0	2
HU23	0	0	0	0	1	0	0	0	1	2
HU31	0	0	0	1	1	0	0	0	0	2
ITC3	0	0	0	0	0	0	1	0	1	2
ITF2	0	1	0	0	1	0	0	0	0	2
ITH1	0	0	0	0	1	1	0	0	0	2
ITH3	0	0	1	0	0	0	1	0	0	2
ITH4	0	0	0	0	0	0	1	0	1	2
ITI4	0	0	0	0	1	0	1	0	0	2
NL21	0	0	0	0	0	1	0	1	0	2
NL22	0	0	0	0	0	1	0	1	0	2
NL23	0	1	0	0	0	1	0	0	0	2
NL42	0	0	1	0	0	0	0	0	1	2
PL21	0	0	0	1	0	1	0	0	0	2
PL22	0	0	0	0	0	1	1	0	0	2
PL42	0	1	0	1	0	0	0	0	0	2
PL52	0	1	0	1	0	0	0	0	0	2
PL62	0	0	0	1	1	0	0	0	0	2
PL71	0	0	1	0	0	1	0	0	0	2
PL91	0	0	0	1	0	1	0	0	0	2
PL92	0	0	1	1	0	0	0	0	0	2
RO31	0	0	1	0	1	0	0	0	0	2
SE11	0	0	0	0	0	1	0	1	0	2
SE12	0	0	0	0	0	1	0	1	0	2
SE21	0	1	0	0	0	0	0	0	1	2
SE22	0	0	0	0	0	1	0	0	1	2
SE33	0	0	1	0	0	0	0	0	1	2
SI04	0	0	0	0	0	1	0	1	0	2
SK02	1	1	0	0	0	0	0	0	0	2
SK04	1	1	0	0	0	0	0	0	0	2
AT21	0	0	0	0	0	0	0	0	1	1
AT32	0	0	0	0	0	0	0	1	0	1
BE21	0	0	0	0	0	0	0	1	0	1
BG32	0	0	0	0	0	0	0	0	1	1
BG41	0	0	0	0	0	1	0	0	0	1
CY00	0	0	1	0	0	0	0	0	0	1
CZ01	0	0	0	0	0	1	0	0	0	1
DE11	0	0	0	0	0	0	0	1	0	1
DE12	0	0	0	0	0	0	0	1	0	1
DE14	0	0	0	0	0	0	0	1	0	1
DE21	0	0	0	0	0	0	0	1	0	1
DE25	0	0	0	0	0	1	0	0	0	1

DE30	0	0	0	0	0	1	0	0	0	1
DE50	0	0	0	0	1	0	0	0	0	1
DE60	0	0	0	0	0	0	0	1	0	1
DEA2	0	0	0	0	0	0	0	1	0	1
DK01	0	0	0	0	0	0	0	1	0	1
DK02	0	0	0	0	0	0	0	0	1	1
EL30	1	0	0	0	0	0	0	0	0	1
ES11	0	1	0	0	0	0	0	0	0	1
ES23	0	0	1	0	0	0	0	0	0	1
ES24	0	0	1	0	0	0	0	0	0	1
ES52	0	1	0	0	0	0	0	0	0	1
ES61	0	1	0	0	0	0	0	0	0	1
ES64	1	0	0	0	0	0	0	0	0	1
FI19	0	0	0	0	0	0	0	0	1	1
FI1B	0	0	0	0	0	1	0	0	0	1
FRJ2	0	0	0	0	0	0	0	1	0	1
FRK2	0	0	0	0	0	0	0	1	0	1
HR02	0	0	0	0	0	0	1	0	0	1
HR05	0	0	0	0	0	0	0	1	0	1
IE04	0	1	0	0	0	0	0	0	0	1
ITC1	0	0	0	0	0	0	1	0	0	1
ITC4	0	0	0	0	0	0	1	0	0	1
ITH2	0	0	0	0	0	0	0	0	1	1
ITH5	0	0	0	0	0	0	1	0	0	1
ITI1	0	0	0	0	0	0	1	0	0	1
LT01	0	0	0	0	0	1	0	0	0	1
LT02	0	0	0	0	0	0	0	1	0	1
MT00	0	0	0	0	0	1	0	0	0	1
NL32	0	0	0	0	0	1	0	0	0	1
NL35	0	0	0	0	0	0	0	1	0	1
PL43	0	0	0	1	0	0	0	0	0	1
PL81	0	0	0	1	0	0	0	0	0	1
PL82	0	0	0	1	0	0	0	0	0	1
PT15	0	0	0	0	0	0	0	1	0	1
PT30	0	1	0	0	0	0	0	0	0	1
RO11	0	0	1	0	0	0	0	0	0	1
RO22	0	0	0	1	0	0	0	0	0	1
RO41	0	0	0	0	1	0	0	0	0	1
RO42	0	0	0	0	0	0	0	0	1	1
SE23	0	0	0	0	0	1	0	0	0	1
SK01	0	0	0	0	0	1	0	0	0	1

Notes: A value of 1 indicates that the region belongs to the “Poor Non-Converging (Left Behind)” club for the corresponding indicator, while 0 indicates otherwise. The “Total traps” column reports the total number of dimensions in which the region is classified as lagging.

Source: Author’s elaboration based on Eurostat regional data.

APPENDIX F: CONVERGENCE CLUBS CLASSIFICATION

This appendix presents the classification of regions into convergence clubs for each indicator considered in the analysis. Regions are grouped into four categories—Rich Converging, Poor Converging, Rich Non-Converging, and Poor Non-Converging—based on their initial conditions and convergence dynamics. The figures report the full distribution of regions across quadrants, providing a comprehensive overview of heterogeneity in regional development patterns.

Figure F1. Convergence clubs classification — GDP per capita (PPS)

Convergence Clubs Classification — GDP per capita (PPS)																		
Poor Non-Converging									Rich Non-Converging									
AT11	BE32	BE33	BE34	BE35	DE40	DE93	DED4		BE31	CZ01	DE30	DK04	ES24					
DEE0	DEG0	EL30	EL41	EL42	EL43	EL51	EL52											
EL53	EL54	EL61	EL62	EL63	EL64	EL65	ES13											
ES63	ES64	ES70	FI1D	FRB0	FRC1	FRC2	FRD1		ES30	ES53	HR05	HU11	IE05					
FRD2	FRE1	FRE2	FRF2	FRF3	FRG0	FRH0	FRI2											
FRI3	FRJ1	FRK1	FRM0	FRY1	FRY2	FRY3	FRY4		IE06	ITC1	ITI1	IT01	NL32					
HU22	ITF1	ITF3	ITF4	ITF6	ITG1	ITG2	ITI2											
ITI3	PT20	SK02	SK03	SK04					PL91	RO32	SI04							
BG31	BG32	BG33	BG34	BG41	BG42	CY00	CZ02	CZ03	AT12	AT13	AT21	AT22	AT31	AT32	AT33	AT34	BE10	BE21
CZ04	CZ05	CZ06	CZ07	CZ08	DE80	DED2	DK02	EE00	BE22	BE23	BE24	BE25	DE11	DE12	DE13	DE14	DE21	DE22
ES11	ES12	ES41	ES42	ES43	ES52	ES61	ES62	HR02	DE23	DE24	DE25	DE26	DE27	DE50	DE60	DE71	DE72	DE73
HR03	HR06	HU12	HU21	HU23	HU31	HU32	HU33	IE04	DE91	DE92	DE94	DEA1	DEA2	DEA3	DEA4	DEA5	DEB1	DEB2
ITF2	ITF5	IT02	LV00	MT00	PL21	PL22	PL41	PL42	DEB3	DEC0	DED5	DEF0	DK01	DK03	DK05	ES21	ES22	ES23
PL43	PL51	PL52	PL61	PL62	PL63	PL71	PL72	PL81	ES51	FI19	FI1B	FI1C	FI20	FR10	FRF1	FRI1	FRJ2	FRK2
PL82	PL84	PL92	PT11	PT15	PT19	PT1B	PT1C	PT1D	FRL0	ITC2	ITC3	ITC4	ITH1	ITH2	ITH3	ITH4	ITH5	ITI4
PT30	RO11	RO12	RO21	RO22	RO31	RO41	RO42	SI03	LU00	NL11	NL12	NL13	NL21	NL22	NL23	NL34	NL35	NL36
Poor Converging									Rich Converging									
									NL41	NL42	PT1A	SE11	SE12	SE21	SE22	SE23	SE31	SE32
									SE33	SK01								

Notes: Regions are classified into four convergence clubs based on initial income levels and growth dynamics. The quadrants identify Rich Converging (92 regions), Poor Converging (72), Poor Non-Converging (61), and Rich Non-Converging (18).

Source: Author's elaboration based on Eurostat regional data.

Figure F2. Convergence clubs classification — Labour productivity

Convergence Clubs Classification — Labour Productivity															
Poor Non-Converging								Rich Non-Converging							
BE32	BE34	BG34	DE40	DEA3	DEB1	DEB2	DED5	AT22	AT31	AT32	AT33	BE23	BE24	BE31	
DEF0	EL41	EL42	EL43	EL51	EL52	EL54	EL61								
EL62	EL63	EL64	EL65	ES11	ES13	ES42	ES43	CZ01	DE23	DE25	DE30	DK04	DK05	FI18	
ES52	ES61	ES62	ES70	FI1D	FRE2	FRF3	HU12	FR10	FRB0	FRE1	FRF2	FRG0	FRI1	FRJ1	
HU22	HU32	IE04	ITF2	ITF4	ITF6	ITG2	ITI2	FRJ2	FRK2	FRL0	FRY1	HU11	IE05	IE06	
NL12	NL13	NL23	NL34	PL41	PL42	PL51	PL52	ITC1	ITH1	ITH3	ITH4	ITI1	ITI4	IT01	
PL61	PL63	PT11	PT20	PT30	SE21	SE31	SK02								
SK03	SK04							NL21	NL32	PL91	RO32	SE33			
AT11	AT12	BE35	BG31	BG32	BG33	BG41	BG42	AT13	AT21	AT34	BE10	BE21	BE22	BE25	BE33
CY00	CZ02	CZ03	CZ04	CZ05	CZ06	CZ07	CZ08	DE12	DE13	DE14	DE21	DE22	DE24	DE26	DE27
DE72	DE80	DE93	DED2	DED4	DEE0	DEG0	DK02	DE60	DE71	DE73	DE91	DE92	DE94	DEA1	DEA2
EE00	ES12	FRC2	FRD1	FRH0	FRI2	FRK1	FRY3	DEA5	DEB3	DEC0	DK01	DK03	EL30	EL53	ES21
FRY4	FRY5	HR03	HU21	HU23	HU31	HU33	ITF5	ES23	ES24	ES30	ES41	ES51	ES53	ES63	ES64
IT02	LV00	MT00	PL21	PL22	PL43	PL62	PL71	FI1C	FI20	FRC1	FRD2	FRF1	FRI3	FRM0	FRY2
PL72	PL81	PL82	PL84	PL92	PT15	RO11	RO12	ITC3	ITC4	ITF1	ITF3	ITG1	ITH2	ITH5	ITI3
RO21	RO22	RO31	RO41	RO42	SI03	SI04		NL11	NL22	NL41	NL42	SE11	SE12	SE22	SE23
Poor Converging								SK01	Rich Converging						

Notes: Regions are grouped according to convergence dynamics in labour productivity. The distribution across quadrants is as follows: Rich Converging (73 regions), Poor Converging (63), Poor Non-Converging (58), and Rich Non-Converging (40).

Source: Author's elaboration based on Eurostat regional data.

Figure F3. Convergence clubs classification — High-tech employment

Convergence Clubs Classification — High-tech Employment															
Poor Non-Converging								Rich Non-Converging							
AT34	BE34	BG31	BG34	CY00	CZ04	DE22	DE24	BE21	BE23	BG41	CZ01	DE14	DED5		
DE40	DE73	DE80	DE92	DE93	DE94	DEA1	DEA4								
DEA5	DEC0	DED4	DEF0	DEG0	DK03	DK05	EL43	DK04	EE00	EL30	ES21	FI19	FR10		
EL65	ES13	ES23	ES24	ES42	ES43	ES62	ES70								
FRD2	FRF2	FRF3	FRI3	FRK1	FRY4	HR03	ITF4	FRC2	FRF1	FRJ2	HU11	HU22	IE05		
ITF6	ITG1	ITH3	ITI3	LV00	NL13	NL42	PL41								
PL71	PL72	PL84	PL92	RO11	RO31	SE31	SE32	LT01	NL32	PL51	PL63	RO32	RO42		
SE33								SE11	SI03						

Notes: The classification highlights heterogeneity in technological employment dynamics. Regions are distributed across quadrants as follows: Poor Converging (75 regions), Poor Non-Converging (57), Rich Converging (52), and Rich Non-Converging (26).

Source: Author's elaboration based on Eurostat regional data.

Figure F4. Convergence clubs classification — Life expectancy

Convergence Clubs Classification — Life Expectancy																		
Poor Non-Converging							Rich Non-Converging											
BE34	CZ02	CZ03	CZ05	CZ06	CZ07	CZ08			AT11	BE10	BE21	BE22	BE23	BE24	BE25	BE31	DE22	
DE80	DEA1	DEA5	DEC0	DEE0	DEG0	FRY5			DE30	DE40	DEB2	DK01	DK03	DK04	EL41	EL42	EL52	
									EL54	EL61	ES11	ES12	ES13	ES21	ES22	ES24	ES30	
HU11	HU21	HU31	HU32	PL21	PL41	PL42			ES41	ES51	ES52	ES53	ES61	ES64	ES70	FI19	FI18	
PL43	PL51	PL52	PL61	PL62	PL63	PL72			FI1C	FI1D	FI20	FRF1	FRM0	FRY2	IE04	IE05	IE06	
PL81	PL82	PL84	PL91	PL92	RO21	RO22			ITC2	ITF1	ITF2	ITF3	ITF4	ITH1	ITH2	ITH3	ITH4	
									ITI2	ITI4	MT00	NL11	NL31	NL32	NL41	PT11	PT16	
SI03	SK03								PT17	SE11	SE12	SE21	SE22	SE23	SE31	SE32	SE33	
AT13	BE32	BE33	BE35	BG31	BG32	BG33			AT12	AT21	AT22	AT31	AT32	AT33	AT34	CY00	DE11	DE12
BG34	BG41	BG42	CZ01	CZ04	DE50	DK02			DE13	DE14	DE21	DE23	DE24	DE25	DE26	DE27	DE60	DE71
EE00	EL51	ES63	FRE1	FRY1	HR03	HR04			DE72	DE73	DE91	DE92	DE93	DE94	DEA2	DEA3	DEA4	DEB1
HU12	HU22	HU23	HU33	LT01	LT02	LV00			DEB3	DED2	DED4	DED5	DEF0	DK05	EL30	EL43	EL53	EL62
PL22	PL71	PT20	PT30	RO11	RO12	RO31			EL63	EL64	EL65	ES23	ES42	ES43	ES62	FR10	FRB0	FRC1
RO32	RO41	RO42	SK01	SK02	SK04				FRC2	FRD1	FRD2	FRE2	FRF2	FRF3	FRG0	FRH0	FRI1	FRI2
									FRJ3	FRJ1	FRJ2	FRK1	FRK2	FRL0	FRY4	ITC1	ITC3	ITC4
									ITF5	ITF6	ITG1	ITG2	ITH5	ITI1	ITI3	LU00	NL12	NL13
									NL21	NL22	NL23	NL33	NL34	NL42	PT15	PT18	SI04	
Poor Converging							Rich Converging											

Notes: Convergence clubs for life expectancy reveal strong polarization across regions. The quadrants include Rich Converging (89 regions), Rich Non-Converging (72), Poor Converging (41), and Poor Non-Converging (37).

Source: Author's elaboration based on Eurostat regional data.

Figure F5. Convergence clubs classification — Tertiary education attainment

Convergence Clubs Classification — Tertiary Education																	
Poor Non-Converging								Rich Non-Converging									
AT33	AT34	BG31	BG33	BG34	BG42	CZ02	CZ04	BE22	BE32	BE34	DE30	DED5	DK04				
CZ05	CZ06	CZ07	DE22	DE23	DE24	DE26	DE27	EL52	ES51	ES52	ES53	FR10	FR80				
DE50	DE72	DE80	DE92	DE93	DE94	DEA1	DEA3	FRC1	FRE1	FRF1	FRF3	FRG0	LT01				
DEA4	DEA5	DEB3	DED4	DEE0	DEF0	DEG0	EL41	LT02	LV00	NL11	NL13	NL32	NL41				
EL63	ES42	ES43	ES63	FRM0	FRY2	HU12	HU22	PL21	PL84	RO32	SE12	SE21	SE22				
HU23	HU31	HU32	ITF2	ITF3	ITF4	ITF5	ITF6	SE31	SE32	SI04	SK01						
ITG1	ITH1	ITI2	ITI4	PL62	PT20	RO21	RO31										
RO41																	
AT11	AT22	AT31	BG32	CZ03	CZ08	DE13	DE73	DE91	AT12	AT13	AT21	AT32	BE10	BE21	BE23	BE24	BE25
DEB1	DEB2	DECO	DK05	EL42	EL43	EL51	EL53	EL54	BE31	BE33	BE35	BG41	CY00	CZ01	DE11	DE12	DE14
EL61	EL62	EL64	EL65	ES62	ES70	FRD1	FRD2	FRE2	DE21	DE25	DE40	DE60	DE71	DEA2	DED2	DK01	DK02
FRF2	FRI3	FRK1	FRY1	FRY3	FRY4	HR03	HU21	HU33	DK03	EE00	EL30	ES11	ES12	ES13	ES21	ES22	ES23
ITC1	ITC2	ITC3	ITC4	ITF1	ITG2	ITH2	ITH3	ITH4	ES24	ES30	ES41	ES61	ES64	FI19	FI1B	FI1C	FI1D
ITH5	ITI1	ITI3	MT00	NL12	NL34	NL42	PL22	PL41	FI20	FRC2	FRH0	FRI1	FRI2	FRJ1	FRJ2	FRK2	FRL0
PL42	PL43	PL51	PL52	PL61	PL63	PL71	PL72	PL81	HU11	IE04	IE05	IE06	LU00	NL21	NL22	NL23	PL91
PL82	PL92	PT11	PT15	PT30	RO11	RO12	RO22	RO42	SE11	SE23	SE33						
SI03	SK02	SK03	SK04														
Poor Converging								Rich Converging									

Notes: The distribution of regions across convergence clubs in education is as follows: Poor Converging (76 regions), Rich Converging (66), Poor Non-Converging (57), and Rich Non-Converging (34).

Source: Author's elaboration based on Eurostat regional data.

Figure F6. Convergence clubs classification — NEET rate

Convergence Clubs Classification — NEET Rate															
Poor Non-Converging								Rich Non-Converging							
AT31	BE22	BE24	BE25	BE31	BE34	BG41	CZ01	BE10	BE32	BE33	BE35	BG33	CZ04	EL41	
CZ02	CZ06	DE25	DE30	DE40	DE71	DE80	DE91	EL42	EL53	EL62	ES12	ES43	ES64	FRD2	
DED2	DED5	DEE0	DEF0	DEG0	EE00	ES21	ES30	FR11	FRJ1	FRY1	FRY2	FRY3	FRY4	HU23	
FI1B	FI1C	FRF3	FRK1	HU11	HU12	HU21	HU22	HU31	HU32	ITC3	ITF1	ITF2	ITF3	ITF4	
ITH1	IT01	LV00	MT00	NL11	NL12	NL13	NL21	ITF5	ITF6	ITG1	ITG2	ITI4	PL42	PL62	
NL22	NL23	NL32	NL34	PL21	PL22	PL41	PL51	PL72	RO12	RO22	RO31	RO41	RO42	SK04	
PL63	PL71	PL84	PL91	PT11	RO21	SE11	SE12								
SE22	SE23	SI03	SI04	SK01											
AT12	AT13	AT21	AT22	AT32	AT33	AT34	BE21	BG31	BG32	BG34	BG42	CY00	EL30	EL43	EL51
CZ03	CZ05	CZ07	CZ08	DE11	DE12	DE13	DE14	EL52	EL54	EL61	EL63	EL64	EL65	ES11	ES13
DE22	DE23	DE24	DE26	DE27	DE50	DE60	DE72	ES22	ES23	ES24	ES41	ES42	ES51	ES52	ES53
DE92	DE93	DE94	DEA1	DEA2	DEA3	DEA4	DEA5	ES61	ES62	ES63	ES70	FR12	FRF2	FRJ3	HR03
DEB2	DEB3	DECO	DED4	DK01	DK02	DK03	DK04	HU33	IE04	IE05	IE06	ITC1	ITC2	ITC4	ITH2
FI19	FI1D	FR10	FRB0	FRC1	FRC2	FRD1	FRF1	ITH3	ITH4	ITH5	ITI1	ITI2	ITI3	PL43	PL52
FRH0	FRI1	FRI2	FRJ2	FRK2	FRL0	IT02	LU00	PL61	PL81	PL82	PT15	PT20	PT30	RO32	SK02
NL42	PL92	RO11	SE21	SE31	SE32	SE33		SK03							
Poor Converging								Rich Converging							

Notes: Regions are classified according to convergence patterns in the NEET rate. The quadrants include Poor Converging (70 regions), Poor Non-Converging (61), Rich Converging (57), and Rich Non-Converging (42).

Source: Author's elaboration based on Eurostat regional data.

Figure F7. Convergence clubs classification — Employment rate

Convergence Clubs Classification — Employment Rate													
Poor Non-Converging							Rich Non-Converging						
BE22	BE35	DE80	ES63	FI1C	FI1D	FRB0	BE34	BG41	CY00	CZ01	CZ02	CZ05	CZ06
FRC1	FRC2	FRD1	FRD2	FRE1	FRE2	FRF2	CZ07	CZ08	DE12	DE26	DE30	DE50	DE60
FRF3	FRI1	FRI2	FRI3	FRJ1	FRK1	FRL0	DE71	DE91	DEA2	DEA3	DEA5	DEB1	DEB2
FRY1	FRY2	FRY3	FRY4	HR02	HR03	ITC1	DED2	DEF0	EE00	ES30	ES53	HU11	HU12
ITC2	ITC3	ITC4	ITF1	ITF3	ITF5	ITF6	HU21	HU22	IE04	IE05	IE06	LT01	LV00
ITG1	ITH3	ITH4	ITH5	ITI1	ITI2	ITI3	NL23	NL42	PL41	PL63	PT15	PT1A	PT20
ITI4	PL22	PL61	PL72				PT30	RO32	SK01	SK02	SK03	SK04	

Notes: The classification shows the distribution of regions across convergence clubs in employment. The quadrants include Rich Converging (88 regions), Poor Converging (61), Rich Non-Converging (48), and Poor Non-Converging (46).

Source: Author's elaboration based on Eurostat regional data.

Figure F8. Convergence clubs classification — Gender employment gap

Convergence Clubs Classification — Gender Employment Gap																
Poor Non-Converging									Rich Non-Converging							
AT31	AT32	AT33	AT34	BE21	BE22	BE23	BE24	BE31	EL30	EL42	EL43	EL51	EL52	EL53	EL54	EL61
BE32	BE33	BE35	BG34	DE11	DE12	DE14	DE21	DE22	EL63	EL64	EL65	ES24	ES41	ES42	ES43	ES61
DE24	DE27	DE40	DE60	DE71	DE73	DE80	DE91	DE92	ES62	FRM0	HU11	HU12	HU21	HU22	HU31	HU32
DE93	DE94	DEA2	DEA3	DEB2	DEB3	DED4	DED5	DEE0	HU33	IE06	ITC1	ITC3	ITC4	ITF1	ITF2	ITF3
DEF0	DEG0	DK01	DK03	DK05	EE00	ES12	ES21	ES30	ITF4	ITF5	ITF6	ITH4	ITI4	PL21	PL42	PL43
FI1C	FI20	FRD2	FRE1	FRE2	FRF3	FRG0	FRH0	FRI1	PL52	PL61	PL62	PL63	PL71	PL72	PL81	PL82
FRI3	FRJ1	FRJ2	FRK2	FRL0	FRY2	FRY4	HR05	ITC2	PL84	PL92	RO11	RO12	RO22	RO31	RO41	
IT02	LV00	NL11	NL12	NL21	NL22	NL35	PT11	PT15								
SE11	SE12	SE31	SE32	SI03	SI04											
AT11	AT12	AT13	AT21	AT22	BE10	BE25	BG31		BE34	CZ01	CZ02	CZ03	CZ04	CZ05	CZ06	
BG32	BG33	BG41	BG42	CY00	DE13	DE23	DE25		CZ07	CZ08	DE26	DEA1	DEA4	DEA5	DEB1	
DE30	DE50	DE72	DED2	DK02	DK04	ES11	ES13		DEC0	EL41	EL62	ES23	ES63	ES64	FRF1	
ES22	ES51	ES52	ES53	ES70	FI19	FI1B	FI1D		FRY3	FRY5	ITG1	ITG2	ITH1	ITH2	ITH3	
FR10	FRB0	FRC1	FRC2	FRD1	FRF2	FRI2	FRK1		ITH5	ITI1	ITI2	ITI3	LU00	MT00	NL13	
FRY1	HR02	HR03	HR06	HU23	IE04	IE05	IT01		NL32	NL36	NL41	NL42	PL22	PL41	PL51	
NL23	NL34	PT19	PT1A	PT1B	PT1C	PT1D	PT20		PL91	RO32	RO42	SK01	SK02	SK03	SK04	
PT30	RO21	SE21	SE22	SE23	SE33											
Poor Converging									Rich Converging							

Notes: The distribution across convergence clubs for the gender employment gap highlights persistent disparities. Regions are classified as Poor Non-Converging (78), Poor Converging (62), Rich Non-Converging (55), and Rich Converging (49).

Source: Author's elaboration based on Eurostat regional data.

Figure F9. Convergence clubs classification — Structural composition

Convergence Clubs Classification — Structural Composition																			
Poor Non-Converging										Rich Non-Converging									
AT11	AT21	AT31	AT33	BE22	BE23	BE24	BE25	BE31	BE32	AT13	DE11	DE12	DE14	DE21	DE27	DE30			
BE33	BE35	BG31	BG32	BG33	BG34	BG42	CZ03	CZ04	CZ05										
CZ07	CZ08	DE22	DE23	DE24	DE26	DE72	DE73	DE80	DE91	DE60	DE71	DE94	DEA2	DEA3	DEF0	DK01			
DEB1	DEB2	DEC0	DED2	DED4	DK02	DK05	EE00	EL53	EL63	EL30	ES11	ES21	ES30	ES41	ES51	ES52			
ES12	FI19	FI1C	FI1D	FI20	FRC1	FRC2	FRD1	FRD2	FRE2	ES61	FI1B	FRF1	HU11	IE06	NL22	NL32			
FRF2	FRI2	FRI3	FRK1	FRY1	FRY2	FRY3	FRY4	HR03	HU23										
ITC2	ITC3	ITF1	ITF5	ITF6	ITG2	ITH2	ITH4	ITI2	ITI3	NL36	NL41	PL21	PL41	PL51	PL61	PL63			
NL11	NL12	NL13	NL34	NL42	PL72	RO42	SE21	SE22	SE31	PL91	PT11	RO32	SE11	SE23					
SE32	SE33																		
AT22	AT32	AT34	BE10	BE21	BE34	CY00	CZ01	CZ02		AT12	BG41	CZ06	DE13	DE25	DE40	DE92			
DE50	DED5	DK03	DK04	EL41	EL42	EL43	EL51	EL52		DE93	DEA1	DEA4	DEA5	DEB3	DEE0	DEG0			
EL54	EL61	EL62	EL64	EL65	ES13	ES22	ES23	ES24		FR10	FRB0	FRE1	FRF3	FRG0	FRH0	FRI1			
ES42	ES43	ES53	ES62	ES63	ES64	ES70	FRM0	FRY5		FRJ1	FRJ2	FRK2	FRL0	ITC1	ITC4	ITF3			
HU12	HU21	HU22	HU31	HU32	HU33	IE04	IE05	ITF2		ITF4	ITG1	ITH3	ITH5	ITI1	ITI4	LT02			
ITH1	LT01	LU00	MT00	NL21	NL23	NL35	PL42	PL43		LV00	PL22	PL71	PL81	PL92	RO11	RO12			
PL52	PL62	PL82	PL84	PT15	PT20	PT30	SE12	SI03		RO21	RO22	RO31	RO41	SK02					
SI04	SK01	SK03	SK04																
Poor Converging										Rich Converging									

Notes: The classification reflects convergence dynamics in sectoral structure. Regions are distributed as follows: Poor Non-Converging (82), Poor Converging (67), Rich Converging (47), and Rich Non-Converging (40).

Source: Author's elaboration based on Eurostat regional data.

This series presents the Master's theses in Public Policy and in European Affairs of the Sciences Po School of Public Affairs. It aims to promote high-standard research master's theses, relying on interdisciplinary analyses and leading to evidence-based policy recommendations.

Unpacking Regional Heterogeneity in the EU: the impact of the ERDF on convergence across NUTS 2 regions for the 2014-2020 period

Giulia, Porfiri

Abstract

This thesis investigates whether European Regional Development Fund (ERDF) investments drove regional convergence across economic, social, and labour market dimensions at the NUTS 2 level during the 2014–2020 Multiannual Financial Framework programming period. Drawing on panel data for 244 regions across 27 EU member states, sourced from Eurostat, the ESPON database, and the EU Open Data Platform, the study employs a combination of absolute and conditional β -convergence models, Spatial Durbin Models, and convergence club analysis, incorporating political and institutional controls to account for structural heterogeneity across regions. The results confirm the presence of absolute β -convergence in economic indicators, while convergence remains more limited in the social and labour market dimensions. Crucially, the analysis finds that the observed catch-up process is driven primarily by endogenous structural mechanisms rather than by direct ERDF financial transfers. Institutional quality, economic openness, and the political orientation of national governments further condition convergence outcomes, with their effects varying significantly across dimensions and indicators. Spatial spillovers from neighbouring regions consistently exert a stronger influence on convergence dynamics than direct allocations, while convergence club analysis reveals that structurally lagging regions tend to cluster geographically, with the composition of these clusters varying across dimensions. These findings challenge the one-size-fits-all logic underlying current Cohesion Policy. The thesis proposes three policy recommendations: integrating ERDF objectives with the green and digital transitions; replacing the existing three-tier regional classification with a four-quadrant place-based allocation framework that distinguishes between active catch-up and structural stagnation; and systematically prioritising cross-border and interregional projects to leverage spatial spillover effects.

Key words

β -convergence, European Regional Development Fund (ERDF), NUTS 2 regions, regional heterogeneity, spatial spillovers, cohesion policy.