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PUBLIC INVESTMENT AND REGIONAL DIVERSIFICATION IN EUROPE

An Economic Complexity Perspective

Cátia Sofia Pereira Parrinha

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

NOVA Information Management School

Instituto Superior de Estatística e Gestão de Informação

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Master Thesis presented as partial requirement for obtaining the Master’s degree in Data Science and Advanced Analytics, with a specialization in Data Science

Supervised by

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Lisbon, November 2024]

DEDICATION

I want to dedicate this thesis to my family for their support, without whom pursuing my dreams would not have been possible. I especially thank my father, who, if he were alive, would be very proud of me pursuing my dreams and being myself.

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ABSTRACT

While numerous studies have explored whether cohesion funds effectively achieve their primary goal of promoting regional convergence, this study aims to add a new perspective by analyzing the impact of European Union (EU) cohesion funds on the economic trajectories of regions with different complexity levels, focusing on regional and activity complexity. This approach is built on Hausmann and Hidalgo's theories, highlighting the importance of economic complexity and activity relatedness networks in shaping regional development. As regions evolve, their economies diversify into more complex activities related to capabilities and knowledge. It is interesting to explore the role of cohesion funds in stimulating or hindering this complexity growth, examining whether funds help regions diversify into more sophisticated industries or remain in the same sectors over time. Splitting the regions into three groups, less developed, transition, and more developed, an analysis will be held on the impact of the funds on the region's diversification, the level of activity complexity the funds invest in, how it influences new entries and exits, and the impact on economic growth. Finally, two case studies of success and unsuccess for each group of regions will help to give more insight into the path of the drive to success or unsuccess. By analyzing the complexity of regions and industries alongside relatedness metrics and introducing two new measures for regional and activity funding capture ability, the study aspires to clarify how regions develop and evolve. It explores the pathways through which regions might diversify into higher-complexity industries and assesses how cohesion funds influence these development trajectories. The findings will add knowledge of regional economic development and offer practical insights into how public investments can enable sustainable growth and diversification across Europe's diverse regions. This study draws on a dataset of 231 NUTS-2 regions across the 27 EU countries over ten years, using industrial data to assess the complexity of regional economic activities. The practical implications of this research are important, as they can guide policymakers in making decisions about regional development and economic policy.

KEYWORDS

Economic Complexity; Product Space; Innovation Economics; Economic Growth; Economic Development; Public Investment; European Funds

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LIST OF ABBREVIATIONS AND ACRONYMS

AFC	Activity Fund Capture
ARDECO	Annual Regional Database of the European Commission
CF	Cohesion Fund
EAFRD	European Agricultural Fund for Rural Development
EC	European Commission
ECI	Economic Complexity Index
EIB	European Investment Bank
EMU	Economic and Monetary Union
ERDF	European Regional Development Fund
ESIF	European Structural and Investment Funds
ESF	European Social Fund
EU	European Union
FIFG	Financial Instrument for Fisheries Guidance
GDP pc	Gross Domestic Products Per Capita
GDP PPS pc	Gross Domestic Products in Purchasing Power Standards per inhabitant
GNI	Gross National Income
IAFC	Industrial Activity Fund Capture
ICI	Industrial Complexity Index
IRFC	Industrial Regional Fund Capture
MS	Member States
PCI	Product Complexity Index
PS	Product Space
RCA	Revealed Comparative Advantage
RFC	Regional Funds Capture

RICI	Regional Industrial Complexity Index
SBS	Structure of Business Statistics

1. INTRODUCTION

Since the beginning, the European Union (EU) has aimed to promote balanced economic growth and reduce regional disparities. To achieve this, the European Commission (EC), in collaboration with Member States (MS), designs a multiannual financial framework that guides the allocation of the European Structural and Investment Funds (ESIF). These funds, which are the heart of the EU's cohesion policy, play a crucial role in promoting sustainable economic development, employment, social protection, and European competitive growth (Becker et al., 2018; Melecký, 2018). However, economic and social disparities persist across EU regions, maintaining the interest in the debate on the effectiveness of cohesion policy in stimulating regional economic and social convergence.

This study contributes to this discussion by exploring the impact of EU cohesion funds on different region’s economic complexity and development paths. Drawing on Hausmann and Hidalgo (Hausmann et al., 2013) Economic Complexity and Product Space, this thesis investigates the role of EU funds in promoting regional economic and knowledge diversification into more sophisticated, high-value activities or if, instead, they have reinforced well-known disparities between regions.

Higher-income regions, which retain more developed knowledge infrastructure, are usually better placed to benefit from innovation and diversification opportunities, potentially deepening regional inequalities (Asheim & Gertler, 2005; Audretsch & Feldman, 1996).

Building on economic complexity theory, Smart Specialization proposes a framework for regional development that aims to promote feasible, complex, and desirable activities due to their relatedness to established capabilities. Smart Specialization offers regions a strategic approach to maximize the impact of development policies while reducing the risk of not achieving sustainable and structural growth (Balland et al., 2019; Boschma, 2014).

Hence, the central goal of this thesis is to provide an exploratory analysis of the potential to intersect the methods of Economic Complexity to better understand the current Cohesion policies and funds at the EU level. To achieve such a goal, we address three main questions:

1. Which regions receive more cohesion funds, are these fund allocations aligned with economic complexity? The first part of the results will delve into this question.
2. What types of activity are supported by EU funds, are they of high or low complexity? The second part of the results will examine this aspect.
3. How do cohesion funds influence economic growth in each region, fostering sustainable regional development? Furthermore, how are these effects linked to complexity and relatedness? The final part of the results will focus on this analysis.

This thesis is organized into four additional chapters. Chapter 2 provides a thorough literature review covering EU cohesion policy, economic growth, and complexity theories. Chapters 3 and 4 summarize the data sources and methodology, detailing the dataset of 231 NUTS-2 regions across the EU27 over ten years, capturing regional activity complexity and economic dynamics. Chapter 5 presents the results and analysis, while chapter 6 concludes and discusses limitations, ensuring the validity and reliability of the findings.

2. LITERATURE REVIEW

2.1. European Union convergence context

The European Union (EU) has aimed to reduce economic and social disparities across its regions since the Treaty of Rome in 1957, laying a foundation for economic integration and convergence through the common market based on the free movement of goods, people, services, and capital. Rooted in neoclassical theory, this approach included the establishment of the European Social Fund (ESF) to support labor retention and the European Investment Bank (EIB) to mobilize financial resources, which were initially deemed sufficient for balanced development. However, as integration progressed, disparities between member states grew, exacerbated by the 1970s oil crisis, prompting the EU to enhance its regional policy by creating the European Regional Development Fund (ERDF) and the European Agricultural Fund for Rural Development (EAFRD) reformation (Marinas et al., 2023).

The concept of cohesion was introduced in 1987, embedding principles such as solidarity, concentration, and partnership within regional policy (Paolo et al., 2009). The Maastricht Treaty of 1992 reinforced cohesion policy as a primary objective of the EU, introduced the Economic and Monetary Union (EMU) (Paolo et al., 2009), and created new instruments, such as the Cohesion Fund (CF), aimed at co-financing infrastructure projects in countries with a Gross National Income (GNI) per inhabitant below 90% of the EU average and the Financial Instrument for Fisheries Guidance (FIFG), to modernizing the fisheries sector (Paolo et al., 2009).

The cohesion Policy (CP) of the European Union (EU) has been subject to continuous reforms. The solidarity policy has been one of the pillars since the Maastricht Treaty; in that sense, interventions aimed at enhancing regional economy structure, stimulating social inclusion, and promoting sustainable development (Crucitti et al., 2023). Thus, economic cohesion in the EU is also strongly linked to economic convergence, where less developed regions grow faster than more developed regions, reducing disparities. Hence, such catching up is measured in GDP per capita (Marinas et al., 2023). Regional convergence is seen when lagging regions experience higher growth rates than more developed areas, closing economic gaps (Marinas et al., 2023). Achieving growth in the EU's least developed regions has required significant investment resources, largely from more prosperous member states, establishing CP as a complex fiscal transfer system and promoting a sense of "solidarity" across the EU. With rising concerns over contribution levels from high-income countries, CP reforms increasingly prioritize economic efficiency and effective fund allocation based on "efficient investor" principles (Marinas et al., 2023).

In 1999, the European Council marked a shift in Cohesion Policy for the 2000-2006 program, transitioning from a solidarity approach to an investment framework aimed at balanced economic and social development across EU regions. This change brought a new emphasis on regional competitiveness, with funding allocation criteria expanding beyond the development level to include efficiency, impact, and absorption capacity. Consequently, regions could no longer receive higher financial support solely based on their less-developed status, reflecting a more strategic and results-oriented approach to fund distribution (Marinas & Priotease, 2016).

After 2006, the Lisbon Strategy redefined the EU Cohesion Policy around regional competitiveness (Marinas & Priotease, 2016). The 2007-2013 program focused on fostering a knowledge economy, competitiveness, sustainable employment, research and development of technology, and sustainable development. This shift moved from compensatory support for less developed regions to a forward investment policy aligned with the EU's competitiveness goals (Constantin et al., 2010). Emphasis on regional competitiveness highlighted the capacity of regions to attract, retain, and grow businesses, thereby generating added value locally (Iammarino et al., 2018). This approach also measured a region's attractiveness as an investment and work destination (Programme Implementation 2007-2013, 2013).

The 2014-2020 program merged the regional competitiveness and convergence objectives into the "investment for economic growth and employment" goal, addressing investment needs across less and more developed regions. This change emphasized the importance of meeting competitive challenges in developed regions to achieve EU wide strategic objectives. This program emphasizes urban areas as regional growth poles, integrating "new economic geography" principles that highlight the spatial distribution of economic activities as central to regional development (Baldwin et al., 2003; Krugman, 1991). In this approach, regional clusters arise from economic interdependencies within specific territories, promoting economies of scale, competitive advantages, and higher productivity. However, these clusters often concentrate in central areas, leading to development disparities with peripheral regions (Baldwin et al., 2003). To mitigate this, the EU promotes polycentric regional development, a strategy that involves establishing multiple growth poles in different regions to balance the benefits of economic agglomeration and reduce regional divergence (Meijers et al., 2018).

In the current program, 2021-2027, modernization became the core of the EU’s cohesion policy, aligning with its priorities to lead the transition toward a climate-neutral economy and a digital society (Cohesion 2021/2027, 2023).

This thesis will focus on the last two programs, encompassing data from 2007 to 2020. Specifically, it will examine the funds most closely used to sustain regional economic growth and development and foster innovation - ERDF, ESF, and CF. These are the European Structural and Investment Funds (ESIF), which are more related to the EU cohesion policy, also known as regional policy. Tables 1 and 2 show that some funds work toward common objectives, often aligning to support the same goals.

Table 1 - Funds objectives under the cohesion policy program 2007 – 2013.

2007-2013 Program		
Objectives	**Main Funds**	**Eligible regions**
Ob.1. Convergence (speeding up the convergence of the least-developed Member States and regions)	ERDF, ESF, CF	NUTS II (least developed, GPD/inh.< 75% of average EU GDP/inh.) NUTS II (in transition, phasing out) – transitory support
Ob. 2. Regional competitiveness and employment (strengthening region's competitiveness and attractiveness as well as employment)	ERDF, ESF	NUTS II (more developed which are not eligible under Convergence, with (GPD/inh. > 75% of average EU GDP/inh.) NUTS II (in transition, phasing in) – transitory support
Ob. 3. European Territorial Cooperation (cross-border, transnational and interregional cooperation)	ERDF	NUTS III (cross-border cooperation) All regions (interregional and transnational cooperation)

Source: Marinas et al., 2022, and EU Regulations

Table 2 – Funds objectives under the cohesion policy program 2014 – 2020.

2014-2020 Program			
Objectives		**Main Funds**	**Eligible regions**
Ob. 1. Investments for growth and jobs	1. Strengthening research, technological development and innovation	ERDF	NUTS II (least developed, in transition, more developed)
	2. Enhancing access to, and use and quality of, information and communication technologies		
	3. Enhancing the competitiveness of SMEs		
	4. Supporting the shift towards a low-carbon economy		
	5. Promoting climate change adaptation, risk prevention and management	ERDF CF	
	6. Preserving and protecting the environment and promoting resource efficiency		
	7. Promoting sustainable transport and improving network infrastructures		
	8. Promoting sustainable and quality employment and supporting labour mobility	ESF	
	9. Promoting social inclusion, combating poverty and any discrimination		
	1.0 Investing in education, training and lifelong learning		
	11. Improving the efficiency of public administration		
Ob. 2. European Territorial Cooperation (cross-border, transnational and interregional cooperation)		ERDF	NUTS III (cross-border cooperation) All regions (interregional and transnational cooperation)

Source: Marinas et al., 2022, and EU Regulations

Studies have been trying to understand the impact of cohesion funds on solving the economic disparities in the European Union regions, which remain an open empirical issue. Some initial literature shows different effects of cohesion funds in solving the economic gap (Boldrin & Canova, 2001; Cappelen et al., 2003). Some of them are more optimistic, pointing out the positive impact of the funds in solving this gap (Becker et al., 2018; Cerqua & Pellegrini, 2018; Crescenzi & Giua, 2016, 2018; Di Caro & Fratesi, 2022; Maynou et al., 2016; Mohl & Hagen, 2008; Pinho et al., 2015).

Others point to the idea of the different convergence patterns among European countries and regions, which can be a spatial distribution of specific conditions and factors that can improve the effectiveness of cohesion (Brandsma et al., 2013). One of the main issues in this field of study relates to the 'one size fits all approach' of the EU cohesion policy and the need to reconsider national and regional differences more in-depth (Crescenzi & Giua, 2018; Di Caro & Fratesi, 2022). Di Caro & Fratesi (2022), studied the different effects depending on the level of assistance and the policy impact, finding four regions with different levels of effectiveness of the cohesion policy. Miron & Holobiuc (2020), found different speeds depending on the regions, such as Nort Westen, Central and Eastern, and Southern European countries. They found that the regions belonging to new members increased faster than the Northwestern countries, experiencing a significant convergence speed. Rauhut (2021), who divided the dataset into the first 15 Member states and the new member, reached the same conclusion. Rauhut (2021), found three 'clubs' in per capita output and spatial location, with capital cities and metropolitan areas converging almost four times faster than the rest of the EU.

Although there are no clear criteria at the European level to define convergence, GDP per capita is one of the most used indicators to quantify this process of poor economies catching up to the level of rich economies or the process of reducing the gaps between countries in terms of living standards, called as a real convergence (Miron & Holobiuc, 2020). Regarding real convergence, there are two concepts in the literature (Robert J. Barro and Xavier I. Sala-i-Martin, 2003): β-convergence and α-convergence.

Regarding β-convergence, we are interested in capturing cases where low-income economies grow faster than higher-income ones. Hence, it is a process that concerns a negative relation between the GDP per capita growth rate and the initial GDP per capita, which implies the low-income economy catches up later in terms of per capita income. In the case of α-convergence, if dispersion in levels of per capita income tends to decrease over a group of regions, which consists of the reduction of the standard deviation of the logarithm of GDP per capita or the reduction of the coefficient of variation of GDP per capita (Robert J. Barro and Xavier I. Sala-i-Martin, 2003).

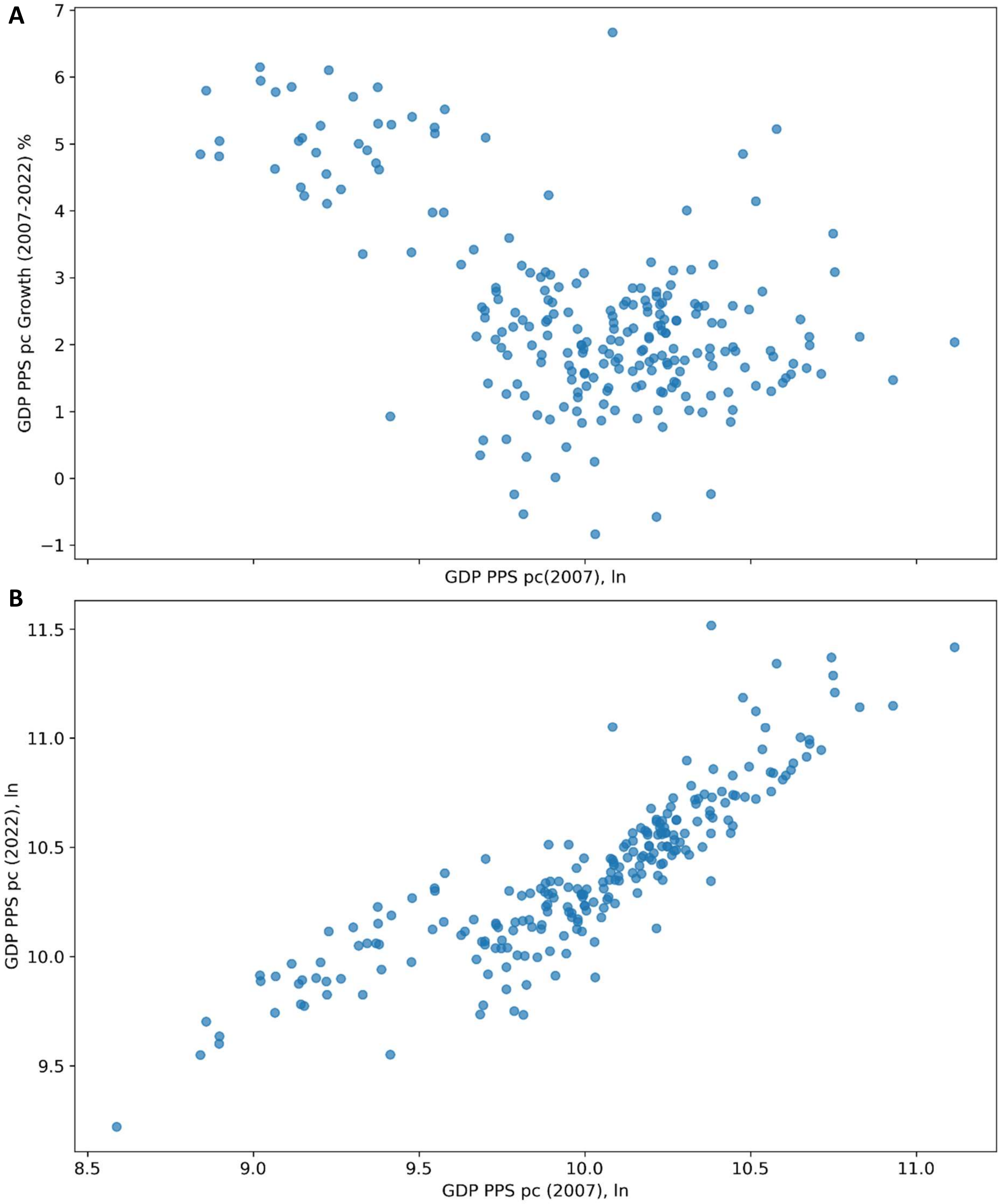

Figure 1 - **A.** The relationship between GDP PPS pc, in the logarithm form in 2007, and the annual GDP growth from 2007 to 2022, in percentage - β-convergence. B**.** The relationship between GDP PPS pc in 2007 and 2022, in logarithm - α-convergence.

Source: Author Calculation based on Annual Regional Database of the European Commission (ARDECO)

Figure 1A illustrates that regions with lower incomes have experienced a higher growth rate than wealthier regions, evidence of β-convergence, which is expected given they also have a broader range of opportunities for economic expansion. However, it is unclear the gap between these regions - α-convergence - has significantly changed from 2007, the start of the first program, to 2022, the last year of expenditures from the last program, as shown in Figure 1B.

To better understand this gap and its evolution over these years, it is possible to reflect it at a regional level. Using the regional eligibility for the ERDF and ESF cohesion funds from programming period 2014-2020, regions was ranked and split into three groups, according the regional GDP PPS per capita average over the years 2007-2009: Less developed regions, where the GDP PPS per capita was less than 75% of the EU-27 regions average; transition regions, where the GDP PPS per capita was between 75% and 90% of the EU-27 regions average; and more developed regions where GDP PPS per capita was more than 90% of the EU-27 regions average (Kotzeva et al., 2015).

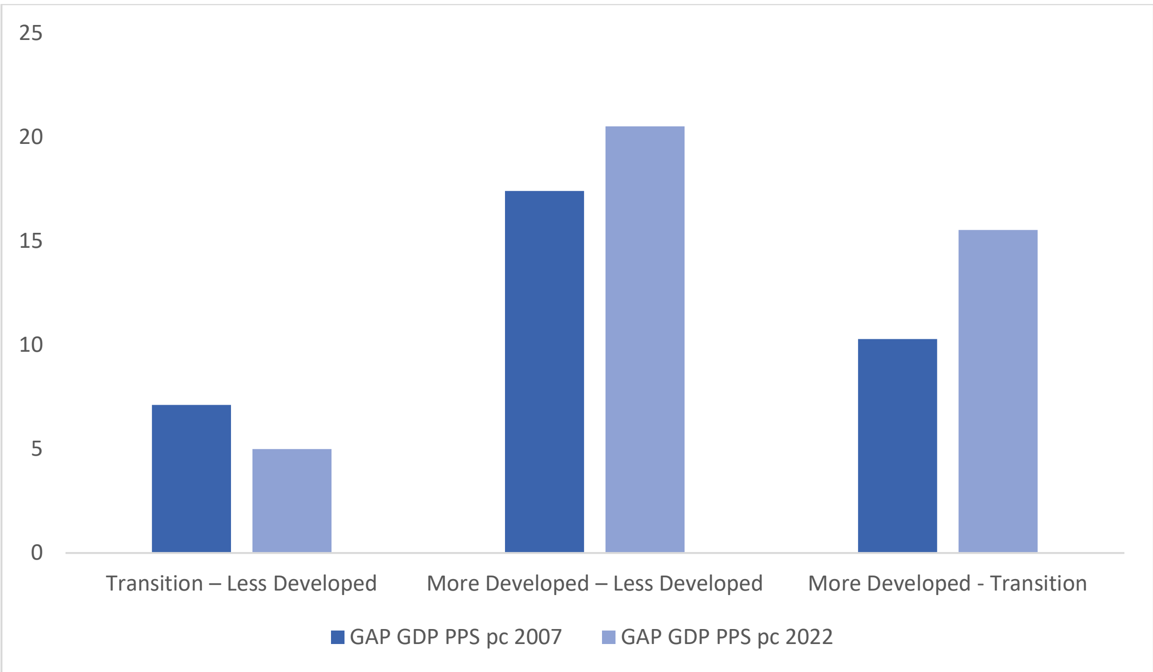

Figure 2 – Absolute GDP PPS pc GAP, from 2007 to 2022, between the three eligible classification regions – Transition and Less Developed, More Developed and Less Developed, More Developed and Transition - in thousands.

Source: Author Calculation based on Annual Regional Database of the European Commission (ARDECO)

Figure 2 displays the GDP PPS per capita gap across the three NUTS2 regional eligibility classifications - Less Developed, Transition, and More Developed - for 2007 and 2022. In absolute terms, Less Developed regions have shown convergence toward Transition regions, with the gap between these two groups constricting over this period. However, Less Developed and Transition regions remain farther from More Developed regions. The gap between the More Developed and Transition and Less Developed regions widened from 2007 to 2022. While it is true that low-income regions may grow faster than high-income regions, more than this rapid growth may be required to ensure sustainable development, balanced income distribution, and an effective real convergence process.

The effects of the cohesion policy on regional economics can depend on different factors, such as the quality of institutions and governance (Di Caro & Fratesi, 2022; Rodríguez-Pose & Garcilazo, 2015), the industrial (Cappelen et al., 2003) and settlement structures (Gagliardi & Percoco, 2017), the territorial capital (Rodríguez-Pose & Fratesi, 2003) or even the human capital (Becker et al., 2013). Public investment can imply returns when used for innovative purposes; on one side, it can indirectly increase private investment (Oleš & Hudcovský, 2024), and on the other side, this innovative process also increases the accumulation of human capital, knowledge, and skills (Aghion & Howitt, 1990).

From the economic growth perspective, this convergence can be read with different theoretical approaches: Keynesian, neoclassical, and evolutionary. However, this dissertation aims to explore the convergence process through the lens of economic complexity theories, determining whether regional convergence is occurring, how it relates to assessing the effectiveness of fund allocation, and with the complexity levels of regions and activities, exploring potential strategies for optimizing cohesion policy.

2.2. ECONOMIC COMPLEXITY AND SMART SPECIALIZATION

Shumpeter J. A. (1943) emphasized innovation and structural change as critical drivers of economic development. He introduced the idea that institutions, entrepreneurs, and technological changes are central to economic growth and should not work independently, viewing capitalism as an evolutionary process characterized by continuous innovation and creative destruction. Modern innovation economists emphasize that economic growth is driven by knowledge and technological spillovers rather than capital accumulation. They note that innovation clusters spatially, since knowledge is difficult to transfer across regions, usually in high-income regions. Consequently, these regions enjoy advantages like better human capital and higher knowledge infrastructure (Asheim & Gertler, 2005; Audretsch & Feldman, 1996; Autant-bernard et al., 2007; Feldman, 2016). This idea has led scholars to express concerns that innovation might not always reduce income disparities and could worsen regional income divergence in Europe (Iammarino et al., 2018; Piketty, 2014).

Economic theories explain regional specialization using the availability and relative proportion of productive factors, such as labor, land, human capital, and infrastructure. These theories help explain why higher-income regions specialize in human capital and infrastructure-intensive goods while lower-income regions focus on labor and land-intensive production (Flam & Flanders, 1991). Economic development is typically measured using aggregate metrics like GDP. However, these measurements ignore the nature and changes in space regarding product structures crucial for understanding structural transformation.

Knowledge's tacit nature makes geography a crucial factor in technology development, particularly for complex, high-value innovations that are hard to transfer (Balland & Rigby, 2017; Fleming & Sorenson, 2001; Maskell & Malmberg, 1999). Recent economic complexity research uses that product structure to explain that regions are likely to diversify into activities related to their existing. The interconnected nature of these activities, which forms the structure of a region's industrial network, is an aspect that helps measure a region's economic complexity (Hidalgo et al., 2007). Simple activities spread easily but offer limited economic benefits, while complex activities, which are more challenging to disseminate, provide significant competitive and regional advantages (Fleming & Sorenson, 2001). As a result, complex activities are often geographically concentrated (Balland et al., 2020).

Hidalgo (2007), introduced a method using export data to conceptualize development as a network-based diffusion process, measuring product distances based on export probabilities. This approach measures the distance between products based on the likelihood that the same regions export them. It proves that regions tend to diversify by developing products close in the product space to those they already export. Similar regions can face different diversification opportunities based on their proximity to other products. Hidalgo & Hausmann (2009), developed complexity indicators to measure regional knowledge and assess the sophistication of exports, showing that complex economies export diverse, sophisticated goods while simpler economies export primary, widely available products. This relatedness principle also applies to new technologies and occupations (Boschma et al., 2013, 2015; Pinheiro et al., 2022).

This approach changes focus from capital accumulation to structural transformation. Economic diversification into more complex activities reduces economic instability risks and improves income potential. However, this requires challenging structural changes (Felipe et al., 2012). Hidalgo's methods depict specific region's limitations and opportunities, suggesting that complex activities preen to cluster in richer areas (Balland et al., 2020; Balland & Rigby, 2017), potentially deepening regional inequality, as noted by Pinheiro (2022).

In the context of the European Community, a crucial question arises: Can European cohesion policy funds enable low-income regions to step into more complex economic activities?

The smart specialization concept arises because different economic structures can lead to different possibilities for their future development instead of a policy that fits for all regions, from top to down. The goal is for each European region to identify its specific competitive advantages as a basis for prioritizing research and innovation investments. This approach was initialized under objective 1 of the cohesion policy in 2014-2020 and reinforced and updated in the program 2021-2027. The Smart was designed to strengthen regions and discover hidden opportunities. Rather than making regions more specialized or less diverse, this approach uses existing capabilities to build a competitive edge in high-value activities (Balland et al., 2019; Boschma, 2014).

The smart specialization policy framework based on relatedness and complexity, summarized by Balland et al. (2019), offers a path to drive the regional economy into a new policy approach, allowing policymakers to assess where regions can develop new activities using the opportunities in complex knowledge. Activities with high relatedness align closely with a region's existing knowledge base, making their development relatively low-cost and low-risk. These opportunities represent a strategic, feasible path for regional innovation. Conversely, activities with low relatedness are far from current regional knowledge, require additional investment, and have higher risk (Balland et al., 2019; Boschma, 2014).

New activities with higher complexity improve a region's knowledge, whereas less complex activities add little value. The strategic smart specialization framework suggests investments in activities with high complexity and relatedness, known as the "high road" policy, which aims to maximize returns and minimize risk. Another approach considered ineffective suggests pursuing activities that are distant from the region's knowledge and low in complexity. Such investments are risky and unlikely to add regional knowledge, a strategy labeled as a "dead-end" policy. Another option is the "casino" policy, which involves taking high-risk, high-cost suggest adding more complex activities but unrelated activities. Although this approach can yield substantial benefits, it is naturally uncertain. Lastly, the "slow road" strategy invests in related but low-complexity activities. While this path carries minimal risk, it offers only limited gains (Balland et al., 2019)

Therefore, the core idea of the smart specialization framework is that region capabilities shape not only the opportunities for developing new growth paths but also the constraints on those possibilities. Balancing relatedness and knowledge complexity provides a foundation for drafting smart specialization strategies. This approach aligns closely with each region's unique strengths, reducing the risk of the inefficient use of public and even private resources (Balland et al., 2019).

3. DATA

This study analyzes the effects of public investment by employing the latest dataset on regionalized and modeled historic annual EU payments from cohesion funds, published by the European Commission's cohesion open data platform and updated in January 2024. While this dataset contains all programs since 1988, the introduction of cohesion polity, until 2020, the last completed program, the focus will be on the two most recent programming periods: 2007-2013 and 2014-2020, covering the actual 27 EU countries, with the focus on NUTS2 regions, the relevant target areas of EU cohesion policy. The expenditures associated with these programs were spent between 2007 and 2022, as illustrated in Figure 3. This analysis will use modeled annual expenditure rather than annual payments, as the European Commission improved this data to more accurately reflect real expenditure, which typically occurs before the EU payments.

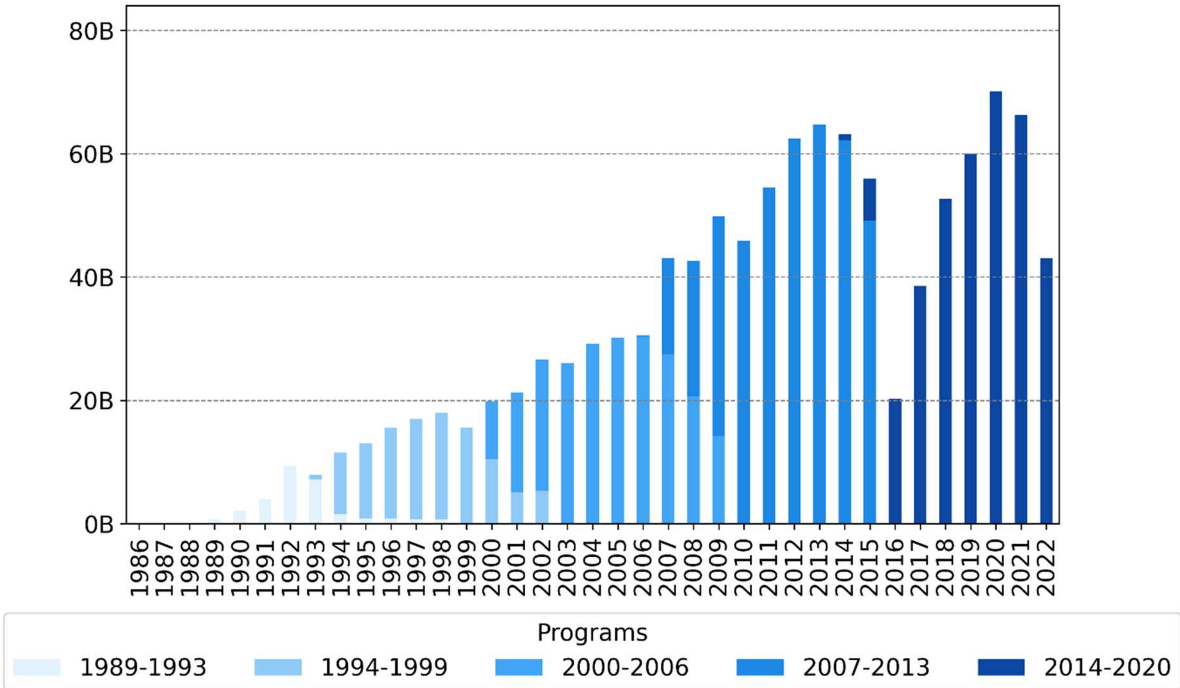

Figure 3 – Annual Modeled expenditure of ERDF, ESF, and CF Funds by program for the 27 EU countries.

Source: European Commission's Cohesion Open data

The most significant expenditure fund is the European Regional Development Fund (ERDF), as illustrated in Figure 4, set to promote economic, social, and territorial cohesion within the European Union. The ERDF explicitly promotes regional economic growth and development, which the main objectives of the last program in the analysis are innovation, research, and the digital agenda, as well as the support of entrepreneurs and the low carbon economy. Complementing the ERDF, the Cohesion Fund (CF) seeks to support the EU's economic, social, and territorial cohesion, while the European Social Fund (ESF) focuses on supporting employment initiatives. These funds share common objectives, as shown in tables 1 and 2, making them a legible focus for this analysis.

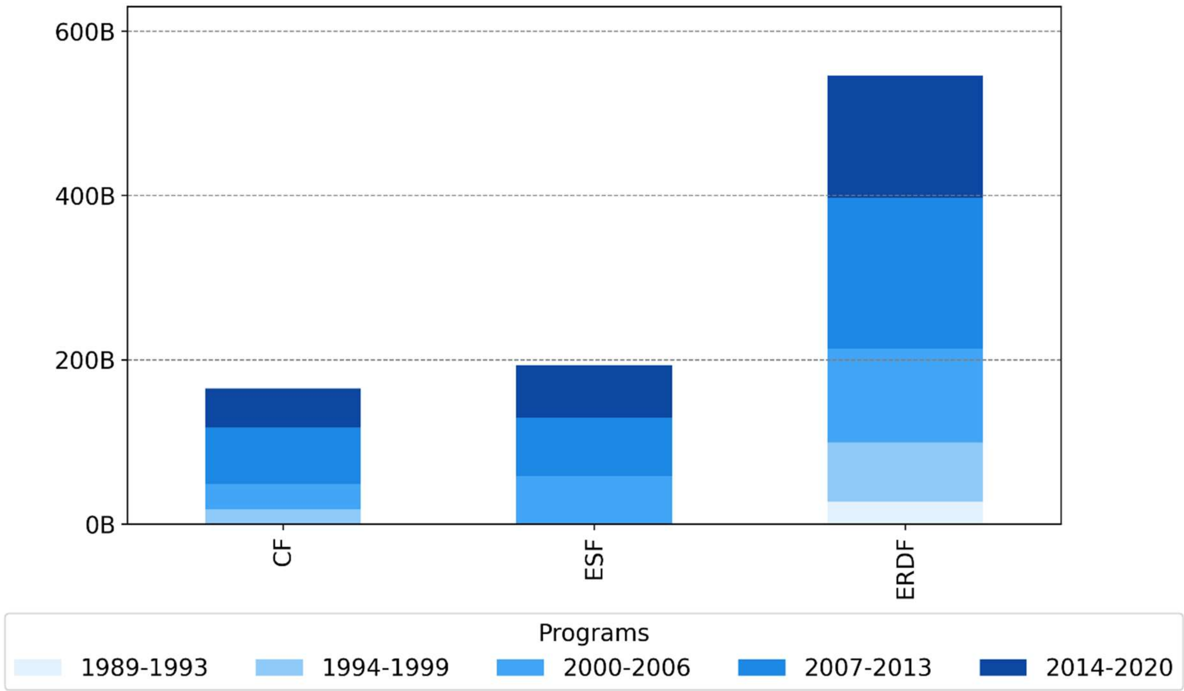

Figure 4 – Total expenditures by ERDF, ESF, and CF Funds and programs for the 27 EU countries.

Source: European Commission's Cohesion Open data

The complexity analysis, an essential part of this study, draws on occupation dataset covering the 27 EU countries. This dataset, employed in studies by Pinheiro (2022), is crucial for assessing regional diversity and the complexity of activities.

The occupation data to measure industrial complexity is sourced from the Structure of Business Statistics (SBS) of the Statistical Office of the European Union and encompasses 68 industry classes (two-digit NACE, Rev. 2) in 235 NUTS-2 regions. To mitigate the noise and outliers in the dataset, a three-year moving average was applied to smooth it. The dataset began in 2008. However, using a three-year moving average, the analysis start from 2010 and extend through 2019. This period accounts for disruptions caused by the COVID-19 pandemic, thus covering a total of 10 years.

An additional dataset for NUTS-2 European regions was obtained from the Annual Regional Database of the European Commission (ARDECO) to complement the analyses. It includes GDP (Gross Domestic Product) measured in PPS (Purchasing Power Standards) per capita, which eliminates differences in price levels and allows for meaningful comparisons between regions of varying absolute sizes.

All NUTS2 regions were converted to the 2010 classification during the data preprocessing. This step was required to prevent potential information loss and ensure comparability across all variables. Standardizing the classification preserved the data's integrity and improved the analysis's accuracy. However, this process resulted in some missing values for the main analysis period in regions like Ireland, where the change in NUTS2 in 2016 did not result in a division nor an aggregation but in a different selection region criterion, which was subsequently excluded from this analysis. In this process, the analysis ended with 231 regional NUTS2. All NUTS Metadata information was taken from Eurostat. Figure 5 reveals an initial idea from the collected data: regions with lower GDP PPS per capita received more funds during the analysis period. This correlation is expected, as GDP per capita is the main criterion for eligibility to receive funds.

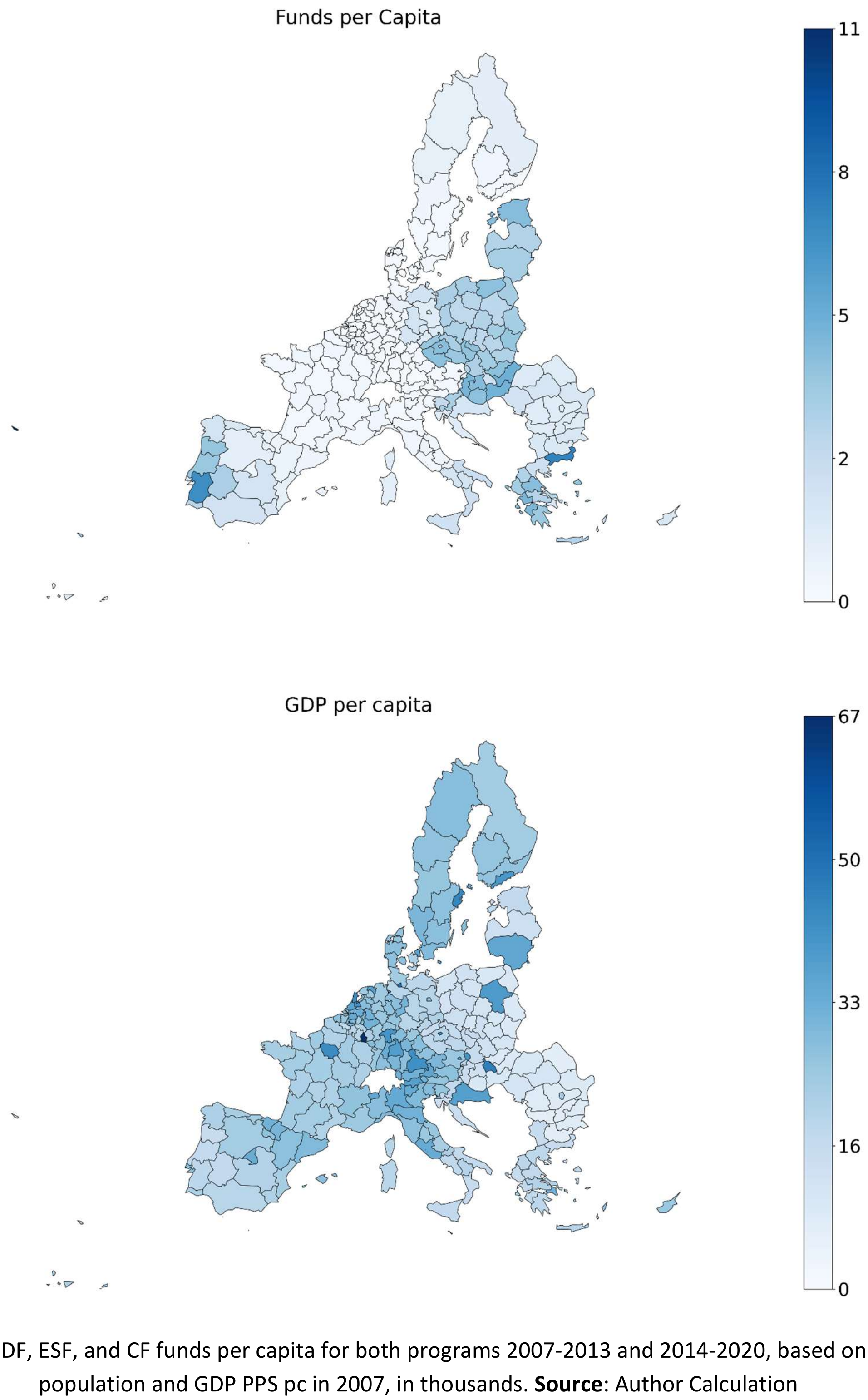

Figure 5 - ERDF, ESF, and CF funds per capita for both programs 2007-2013 and 2014-2020, based on the 2007 population and GDP PPS pc in 2007, in thousands. **Source**: Author Calculation

4. METHODOLOGY

4.1. Regions and Activities Complexity

The methods employed in this study, using Hausmann (2013) and Pinheiro (2022) as a reference, measure the complexity of knowledge of activities. This involves identifying the diversity of activities within a region, the region's knowledge/capabilities, and the ubiquity, the number of regions with knowledge/capabilities required by an activity.

This study uses the revealed comparative advantage (RCA) (Balassa, 1965), that provides a perspective on the distribution of activities across regions:

$$RCA_{r,a} = \frac{X_{ra}}{\Sigma_r X_{ra}} \Big/ \frac{\Sigma_a X_{ra}}{\Sigma_{r,a} X_{ra}} \tag{1}$$

where X_{ra} is a rectangular matrix that summarizes the intensity of an activity (Industry) in a region *r*.

A region *r* is considered to have an RCA in activity when $RCA_{ra} \geq 1$.

Balassa's definition says that a region has a location quotient or a revealed comparative advantage in an activity if it produces more than its 'fair share', equal to the share of the total region's production that the activity represents. Lower values may indicate low productivity or quality, hence knowledge deficiencies.

RCA are presented as a matrix, where rows will be the regions r and columns will be the activities a. A specialization matrix (M) will have one if the region has the activity (RCA > 1) and 0 otherwise.

So, to binarize, the RCA input is needed.

$$M_{r,a} = \begin{cases} 0 \; if \; RCA_{r.a} < R \\ 1 \; if \; RCA_{r,a} > R \end{cases} \tag{2}$$

Where R = 1.

This is a way to remove excess variation by focusing on the significant presence $M_{r,a} = 1$ and the absences $M_{r,a} = 0$.

The marginals of $M_{r,a}$ count the number of activities present in a region (diversity) and the number of regions where activity is present (ubiquity).

$$k_r = \sum_a M_{ra} = diversity \quad (3)$$

$$k_a = \sum_r M_{ra} = ubiquity \quad (4)$$

The ECI and PCI are based on the idea that the complexity of a region (ECI) reflects the average complexity of its activity. Similarly, the complexity of activities (PCI) reflects the average complexity of regions with comparative advantages in these activities. This reciprocal relationship leads to the iterative process described below:

$$ECI_r = \frac{1}{k_r} \sum_a (M_{ra}, PCI_a) \quad (5)$$

$$PCI_a = \frac{1}{k_a} \sum_r (M_{ra}, ECI_r) \quad (6)$$

Replacing (6) into (5) provides an eigenvalue equation ($\vec{K}$) whose solution is the ECI of a region. Furthermore, replacing (5) into (6) provides an eigenvalue equation ($\vec{Q}$) known as PCI of an activity. It is tradition to present ECI and PCI as Z-scores:

$$ECI_r = \frac{\vec{K} - mean(\vec{K})}{stdev(\vec{K})} \quad (7)$$

$$PCI_a = \frac{\vec{Q} - mean(\vec{Q})}{stdev(\vec{Q})} \quad (8)$$

ECI measures the accumulated knowledge in a region, and PCI evaluates the knowledge intensity of a particular activity. ECI values greater than zero indicate regions whose complexity exceeds that of the average region in the dataset; the same idea applies to PCI.

Since this analysis is based on the occupation dataset reflecting Industries, as Pinheiro (2022) did in his analysis, the regional complexity indicators, such as ECI, will be referred to as the Regional Industrial Complexity Index (RICI). For PCI, the same logic applies to the Industrial Complexity Index (ICI).

Through the iteration presented in equations (5) and (6), followed by the standardization, the PCI and ECI for Industries in European regions were estimated annually from 2010 to 2019.

Table 3 highlights the complexity of the top and bottom ten regions. Regions with high RICI scores, such as Stockholm in Sweden, and regions from the Netherlands, such as Noord-Holland, Utrecht, Flevoland, and Belgium's Prov. Vlaams-Brabant and Brussels are among the top ten regions regarding complexity level. On the other hand, several regions in Romania and the Czech Republic exhibit low RICI scores.

Table 3 – Top and Bottom Ten Regional Industrial Complexity Index (RICI), 2019.

#	NUTS-2	Region	RICI
1	NL32	Noord-Holland	2.59
2	BE24	Prov. Vlaams-Brabant	2.35
3	BE10	Bruxelles	2.23
4	SE11	Stockholm	2.10
5	DK01	Hovedstaden	2.07
6	DE60	Hamburg	2.04
7	PT17	Lisboa	1.99
8	NL31	Utrecht	1.96
9	DE30	Berlin	1.95
10	NL23	Flevoland	1.85
…	…	…	…
222	SI01	Vzhodna Slovenija	-1.44
223	CZ07	Stredni Morava	-1.46
224	CZ03	Jihozápad	-1.48
225	RO31	Sud-Muntenia	-1.49
226	PT11	Norte	-1.49
227	CZ05	Severovýchod	-1.55
228	CZ04	Severozápad	-1.58
229	RO42	Vest	-1.66
230	RO12	Centru	-1.68
231	PL43	Lubuskie	-1.70

Table 4 – Top and Bottom Ten Industrial Complexity Index (ICI), 2019.

#	Industry	ICI
1	Motion picture, video and television	2.17
2	Activities of head offices	1.95
3	Air transport	1.94
4	Advertising and market research	1.82
5	Computer programming consultancy	1.59
6	Programming and broadcasting	1.47
7	Travel agency, tour operator	1.42
8	Publishing	1.40
9	Telecommunications	1.30
10	Scientific research and development	1.25
…	…	…
59	Manufacture of rubber and plastic	-1.13
60	Other Manufacturing	-1.14
61	Manufacture of wood	-1.15
62	Mining support services	-1.18
63	Manufacture of metal products	-1.41
64	Manufacturing of furniture	-1.36
65	Manufacture of leather	-1.41
66	Manufacture of textiles	-1.56
67	Manufacture of wearing apparel	-1.57
68	Mining of coal and lignite	-1.58

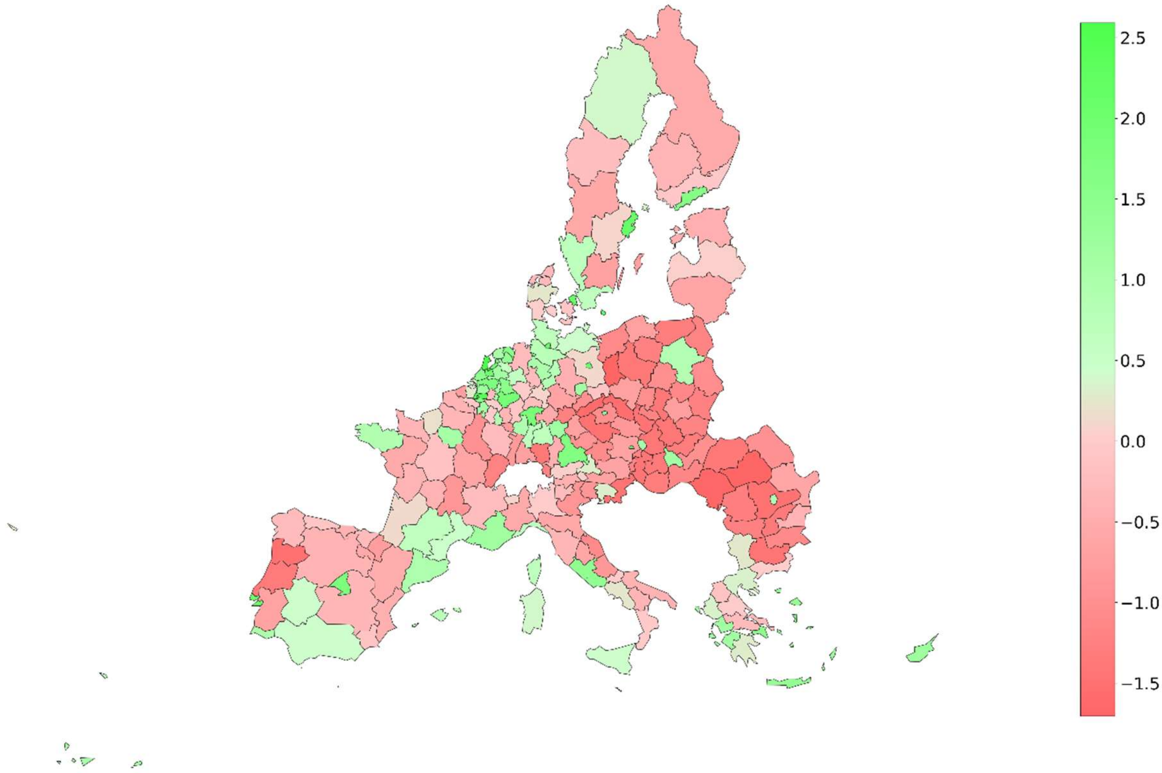

Figure 6 - RICI for 231 NUST2 European regions, from low complexity (red) to high complexity (green), 2019.

The map from Figure 6 illustrates the RICI scores from European regions for 2019, arranged from regions with low complexity (displayed in red) to those with high complexity (displayed in green). The color gradient highlights the varying levels of complexity in activities among these regions, providing a visual representation of their relative positions.

Table 4 displays the top and bottom ten complexity activities, revealing that activities related to information and communication (motion picture, video and television, programming and broadcasting, telecommunications, computer programming, consultancy), professional, scientific, and technical activities (activities of head office, scientific research and development, advertising and market research), transporting and storage (air transport) and administrative and support service activities (travel agency) rank highest, denoting areas where only a few regions can attain comparative advantages. In contrast, many European regions reveal comparative advantages, mainly in manufacturing industries. More details about the Nace classification can be consulted in Appendix D.

Hausmann (2006), showed that the type of activity in the region basket influences the income level. In this way, he developed new measures to describe the degree of sophistication of an activity and a region. The same approach can be used for any other indicator. Hausmann used it with the GINI index to find the relationship between regions and activities and its structure on inequality reduction.

This analysis will use the same logic but with a new indicator, the Funds per capita (Funds pc). The annual fund expenditures are related to the annual population, which creates a relative measure to compare all regions. This indicator will estimate which activities are more likely to receive more funds and whether they relate to complex or simpler activities.

Called it as the Activity Fund Capture (AFC), the funds each activity can capture, formally, we have:

$$AFC_a = \frac{1}{N_a} \Sigma_r M_{ra} S_{ra} Fundspc_r \tag{9}$$

Where Fundspc is the funds per capita each region *r* receives, S_{ra} is the share of region's *r* activity *a*, represented by:

$$S_{ra} = \frac{X_{ra}}{\Sigma_{a'} C_{ra'}} \tag{10}$$

Where X_{ra} is the activity *a* in region *r* and $\Sigma_{a'} C_{ra'}$ the total of activities in region *r*.

N_a is a normalizing factor that ensures AFCs is the weighted average of the Fundspc:

$$N_a = \Sigma_r M_{ra} S_{ra} \tag{11}$$

AFC is calculated by the weighted Funds per capita of the regions with that activity, RCA >1, to distinguish the regions with that activity from those without. The high value of AFC indicates that the activity exists in a region with high funds. As made before, the occupation dataset will be referred to as the Industrial Activity Fund Capture (IAFC). AFC was normalized and presented as Z-scores to have values with the same logic as the ICI. Positive values for activities with a high capacity to capture funds and negative values for activities that receive less funds.

Table 5 highlights which industrial activities have a greater or lesser capacity to attract funds (IAFC). Sectors like mining, manufacturing, water supply (sewerage), and construction (civil engineering) are more likely to be in regions that receive more funds, increasing their probability of securing additional funds. In contrast, activities with less capacity to attract funding include sectors like administrative and support services (employment activities), professional, scientific, and technical activities (activities of head office, scientific research), Information and communication (publishing activities, motion picture, video and television, computer programming) and transporting and storage (air transport).

Table 5 - Top and Bottom Ten industrial activities with capacity to capture funds (IAFC), 2019.

#	Industry	IAFC
1	Mining of coal and lignite	2.40
2	Water collection, treatment and supply	1.83
3	Sewerage	1.56
4	Manufacture of tobacco products	1.54
5	Manufacture of furniture	1.43
6	Other mining and quarrying	1.40
7	Manufacture of wearing apparel	1.28
8	Mining support service activities	1.27
9	Civil engineering	1.20
10	Manufacture of wood and of products of	1.06
…	…	…
59	Postal and courier activities	-1.14
60	Scientific research and development	-1.16
61	Computer programming, consultancy	-1.32
62	Manufacture of basic pharmaceutical	-1.45
63	Air transport	-1.47
64	Services to buildings and landscape activities	-1.53
65	Motion picture, video and television	-1.56
66	Publishing activities	-1.67
67	Activities of head offices	-1.73
68	Employment activities	-2.13

Comparing these results with ICI, using the reference year of 2019, from the point of view of Industries, it is possible to observe a high negative correlation between an activity's complexity and its ability to capture more funds. As illustrated in Figure 7, more complex activities (high ICI) receive less funds (low IAFC), and less complex activities (low ICI) receive more funds (high IAFC). These patterns can be observed consistently for each year's analysis, as detailed in Appendix A, Figure A6.

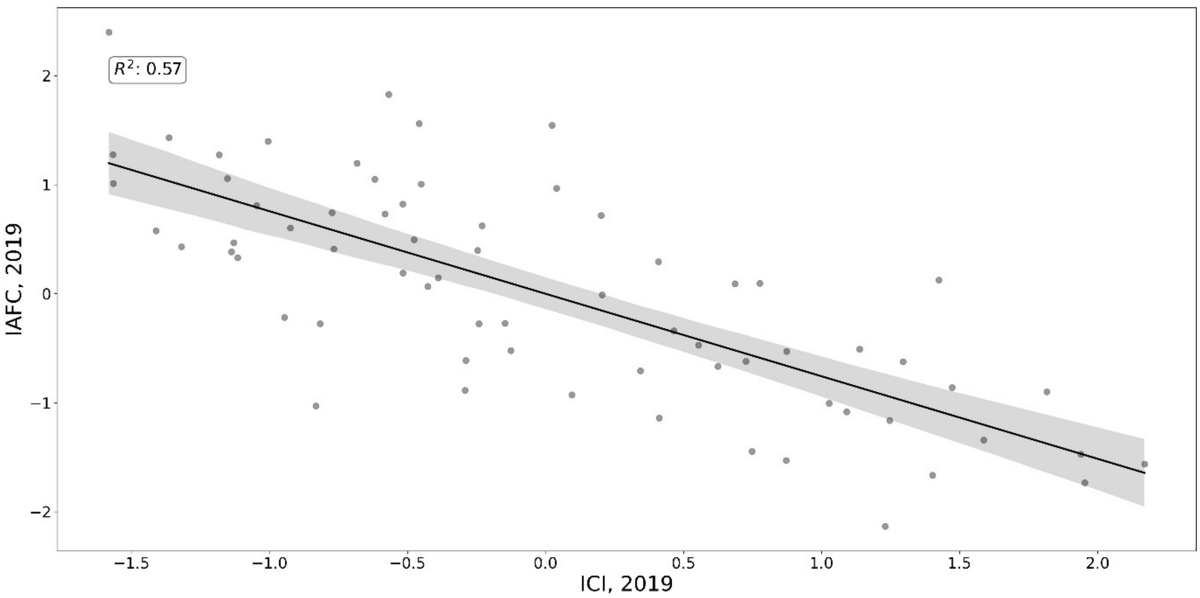

Figure 7 - ICI and IAFC correlation, 2019.

For a baseline comparison at the region's level, it is possible to call the Regional Funds Capture (RFC) the average Funds level of a region based on the basket activities. RFC is calculated by the average funds of the region's competitors, using a weighted average of the AFC of a region's basket activity, where the weights are the region's activity shares.

$$\mathrm{RFC}_r = \Sigma_a \frac{X_{ra}}{\Sigma_{a'} X_{ra'}} AFC_a \tag{12}$$

In this case, the occupation dataset will be called the Industrial Regional Fund Capture (IRFC). IRFC was also normalized to have values presented as Z-scores, with the same logic as the RICI: positive values for regions with a high capacity to capture funds and negative values for regions that can receive fewer funds.

Table 6 emphasizes regions with different capacities to attract funds. From an industrial perspective (IRFC), regions in Romania, such as Sud-Vest Oltenia, Sud-Muntenia, and Centru, Śląskie, and Warmińsko-Mazurskie in Poland, and Severozapaden, and Yuzhen Tsentralen in Bulgaria, show a high capacity to capture funds. Conversely, regions with less capacity to attract funds include Drenthe, Flevoland, Groningen, Utrecht, Noord-Holland, and Noord-Brabant in the Netherlands, along with Brussels, Prov. Vlaams-Brabant, and Prov. Brabant Wallon in Belgium.

Table 6 - Top and Bottom Ten industrial regions with the capacity to capture funds (IRFC), 2019.

#	NUTS-2	Region	IRFC
1	PL11	Śląskie	3.24
2	RO41	Sud-Vest Oltenia	2.75
3	CZ04	Severozápad	2.63
4	RO31	Sud - Muntenia	2.08
5	EL11	Anatoliki Makedonia, Thraki	1.90
6	RO42	Vest	1.65
7	BG31	Severozapaden	1.65
8	RO12	Centru	1.64
9	PL62	Warmińsko-Mazurskie	1.60
10	BG42	Yuzhen tsentralen	1.58
…	…	…	…
222	BE10	Bruxelles	-1.67
223	NL13	Drenthe	-1.71
224	DEA2	Köln	-1.74
225	NL23	Flevoland	-1.74
226	NL11	Groningen	-1.76
227	NL31	Utrecht	-1.83
228	BE24	Prov. Vlaams-Brabant	-2.14
229	NL32	Noord-Holland	-2.18
230	NL41	Noord-Brabant	-2.24
231	BE31	Prov. Brabant Wallon	-2.36

Comparing results with RICI, using the reference year of 2019, it is possible to observe a strong negative correlation between a region's complexity and its ability to attract funding in the industrial sector, as shown in Figure 8. The higher the region's complexity (RICI), the lower the ability to capture funds (IRFC). This suggests that more complex regions tend to receive fewer funds. These patterns remain consistent yearly, as shown in Appendix A, Figure A4.

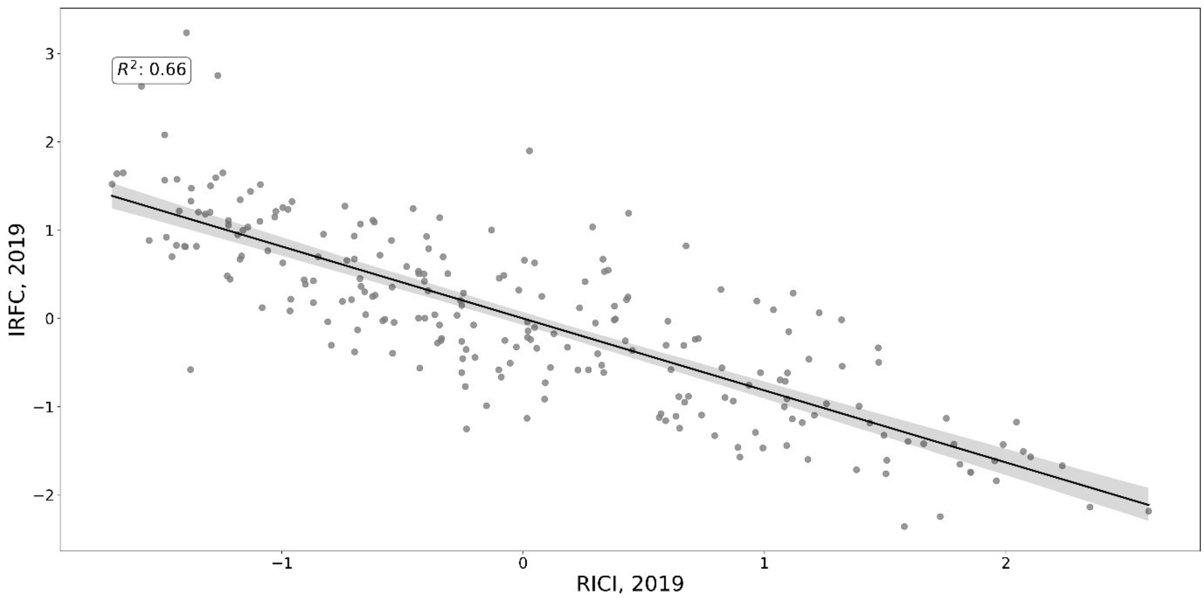

Figure 8 - RICI and IRFC correlation, 2019.

Finally, it is possible to confirm that the IRFC has a positive and moderate correlation with the funds. Figure 9 compares the 2019 IRFC and the total expenditures of funds per capita, showing that the higher the IRFC (high capability to capture funds), the higher the total funds these regions received. These patterns remain consistent yearly, as shown in Appendix A, Figure A5.

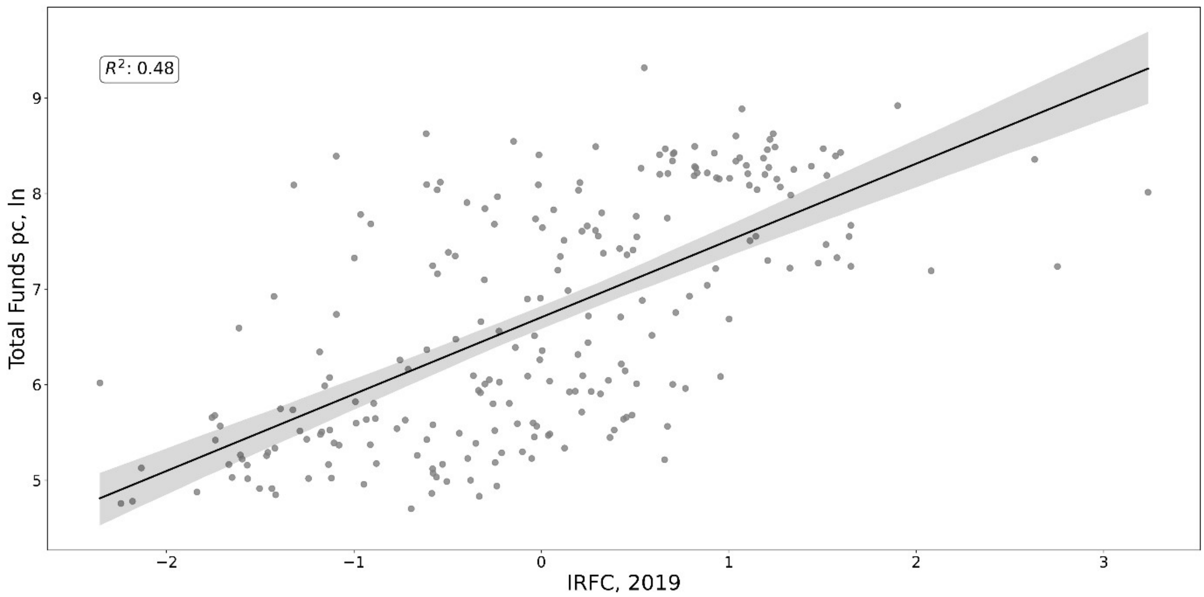

Figure 9 – Correlation of IRFC (2019) and the total fund's expenditure per capita.

4.2. Relatedness Density

To determine the possibility that two activities share similar capabilities, proximity can be quantified by the probability of an activity a, given a', and vice versa. Since the evolution of the economic structure is path-dependent, the Proximity index measures the minimum likelihood that a region holds comparative advantages in activity a, given that it has comparative advantages in activity a'. The group of proximities forms a network connecting pairs of products, known as the product space. It is important to analyze a region's productive structures and understand how a region may enhance its economic complexity. The product space displays that numerous activities naturally cluster into highly interconnected groups of activities, suggesting that the activities within these clusters likely require similar capabilities as Hidalgo et al. (2007) suggested.

For a pair of goods a and a', proximity is defined as:

$$\varphi_{a,a'} = \frac{\Sigma_r M_{ra} M_{ra'}}{\max\left(k_{a,0} k_{a',0}\right)} \tag{14}$$

where:

M_{ra}= 1, region *r* produces activity with RCA >1 and 0 otherwise, and

$k_{a,0}$, is the ubiquity of activity a.

The principle of relatedness posits that a region's likelihood of adopting new economic activities increases with the presence of related activities. This principle highlights path dependencies and forecasts growth or even the decline in regional activities based on relatedness metrics. Relatedness also connects to absorptive capacity, which suggests that a firm's ability to integrate new knowledge depends on its existing related knowledge. Thus, although a region's success in embracing new economic activities is influenced by geographical and cultural proximity, it is also influenced by the cognitive and technological similarities between new and existing activities (C. A. Hidalgo et al., 2018). This concept aligns closely with the literature on industrial clusters, which examines intersectoral connections beyond shared knowledge (Moreno et al., 2005).

To explore how prior productive experiences can benefit other activities, the relatedness density, denoted as ω_{ra}, is calculated. This metric assesses the concentration of similar activities within a region, providing insights into the potential for economic diversification and complexity.

$$\omega_{ra} = \frac{\Sigma_{r'} M_{r'a} \phi_{r'r'}}{\Sigma_{r'} \phi_{r'r}} \tag{15}$$

For the analyzed period, the portfolio of complex activities in the EU was examined by measuring the Pearson correlation between relatedness density and the Industrial Complexity Index (ICI). A positive correlation coefficient indicates that a region is close to complex activities, while a negative correlation coefficient implies proximity to simpler activities. This relationship between complexity and relatedness density can reveal a region's strategic potential for development and its limitations, highlighting its capacity to diversify its economic structure toward more complex or simpler activities (Hartmann et al., 2020; Pinheiro, Balland, et al., 2022; Pinheiro, Hartmann, et al., 2022). Regions with a high density of comparative advantages in related activities are more likely to shift towards more complex activities, thereby increasing regional complexity (C. A. Hidalgo et al., 2018), as shown in Figure 10.

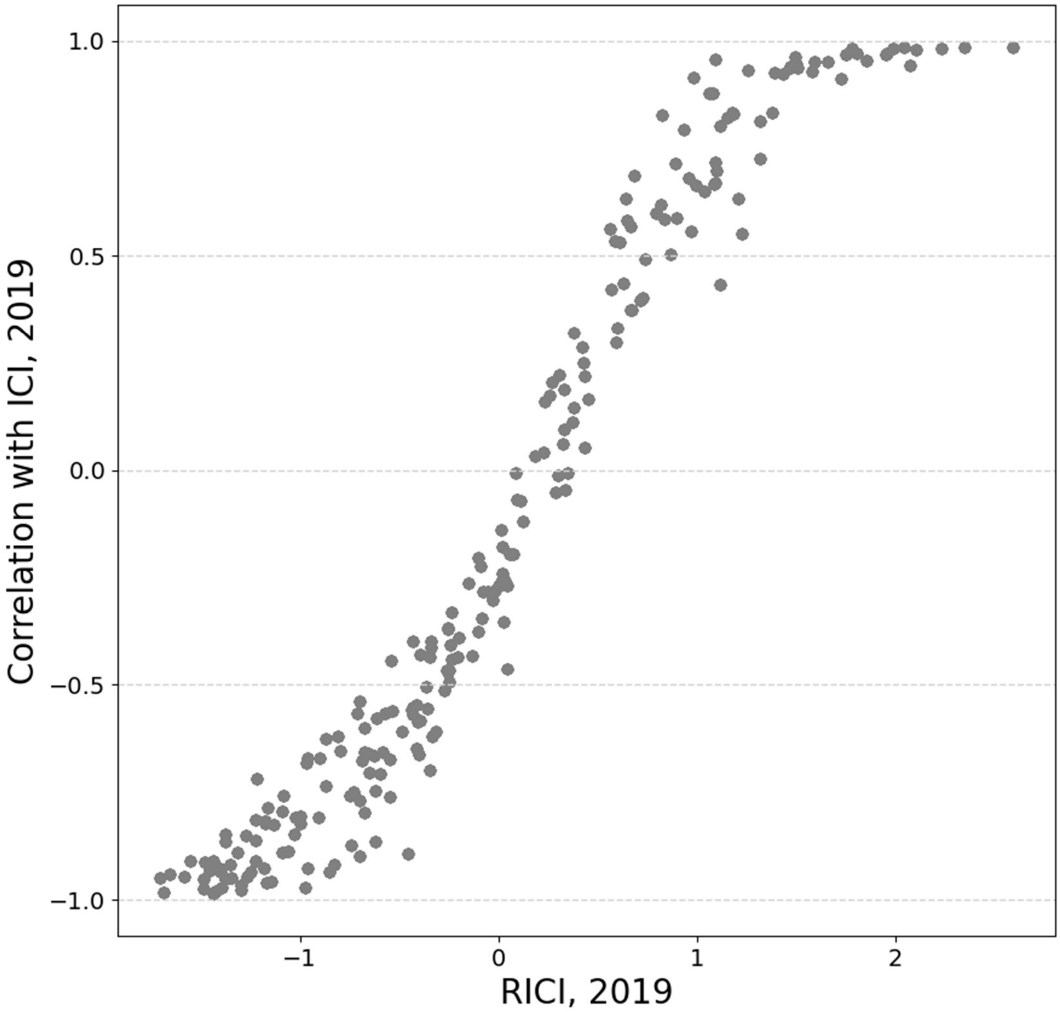

Figure 10 – Correlation between relatedness density and complexity of industries (ICI) as a function of the Regional Industrial Complexity Index (RICI), 2019.

5. RESULTS AND DISCUSSION

The analyses distinguish three categories of eligible regions: less developed, transition, and more developed. The purpose is to understand how regional characteristics influence the allocation and effectiveness of cohesion funds.

The results are organized into three sections:

The first discusses the primary findings on regional complexity and its connection to and impact on the cohesion funds throughout the Industrial Regional Funds Capture (IRFC) indicator.

The subsequent section will concentrate on the activity level, exploring the new indicator of Industrial Activity Fund Capture (IAFC). This indicator will clear the influence of fund allocation on the entry and exit of economic activities and the role of complexity in these dynamics.

The final section evaluates how regional complexity, relatedness, and fund allocation are interlinked with GDP growth across regions and how they contribute to regional economic performance over time. Two case studies for each different group of regions are presented within the smart specialization framework. This analysis evaluates each region's activity portfolio, categorizing activities throughout the RCA mean from the period in the analysis as the initial set of industrial activities (RCA = 1), new entries (0<RCA<1), exits (RCA < 0), and remaining potential new industrial activities (RCA = 0). This section examines these categories to provide deeper insights into the interplay between complexity, relatedness, and fund capture and their implications for regional policy outcomes.

These analyses aim to understand better the European region's strengths and weaknesses in achieving sustainable economic convergence through the cohesion fund, viewed through the lens of complexity.

5.1. REGIONS COMPLEXITY AND COHESION FUNDS

In the European Union, the primary criterion for regional eligibility to receive cohesion funds, such as the ERDF and ESF, is GDP per capita (GDP pc). Figure 11 illustrates the classification of regions based on their eligibility for cohesion funds during the 2014–2020 programming period. Regions were categorized into three groups according to their average GDP PPS per capita from 2007 to 2009: *less developed regions*, with GDP PPS per capita less than 75% of the EU-27 average; *transition regions*, with GDP PPS per capita between 75% and 90% of the EU-27 average, and *more developed regions*, with GDP PPS per capita exceeding 90% of the EU-27 average (Kotzeva et al., 2015). Geographically, less developed or transition regions are predominantly located in the eastern parts of the EU and peripheral areas, such as Portugal, Spain, Italy, and Greece. In contrast, Europe's central and northern parts are generally classified as more developed regions.

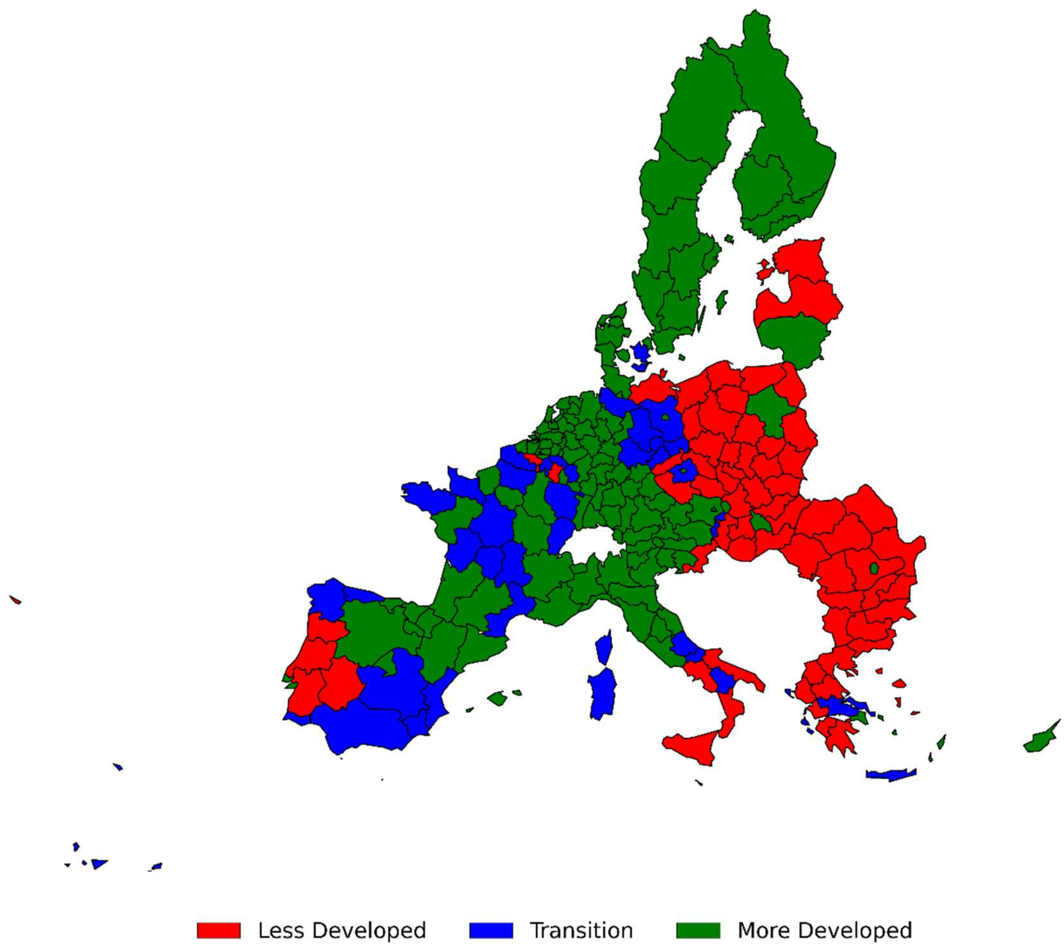

Figure 11 - Map with different eligibility regions, based on the GDP PPS pc over 2007-09. **Red** - Less developed regions with GDP PPS pc < 75 % of the EU 27 average. **Blue** - Transitions regions, with GDP PPS pc ≥ 75% and < 90% of the EU 27 average. **Green** - More developed regions, with GDP PPS pc ≥ 90% of the EU 27 average.

Source: Author Calculation based on Kotzeva et al. (2015) and European Commission's cohesion open data

Figures 12 and 13 delve deeper into the relationship between GDP PPS per capita, the cohesion funds allocated to each region, the Regional Industrial Complexity Index (RICI) for 2019, and its evolution from 2010 to 2019.

Given that cohesion funds are directly linked to GDP, higher-income regions are expected to receive fewer funds, while lower-income regions receive more. This relationship is clear in Figures 12A, 12B, and 13B, where regions classified as less developed demonstrate a higher capability to attract funds than more developed ones.

The literature on economic complexity highlights a pattern where high-income regions diversify into more complex economic activities, while low-income regions usually engage in simpler activities (Hausmann et al., 2013; Pinheiro, Balland, et al., 2022). This trend is reflected in Figure 12C, which reveals less developed regions with negative RICI values on average, transition regions around zero, and more developed regions with positive RICI, on average. Figure 13C also illustrates this pattern, visualizing the relationship between RICI and GDP PPS per capita and how the regions are distributed across these indicators. However, it is important to note that despite this tendency, each group has a high dispersion.

Given the set relation between GDP PPS per capita, cohesion funds, and RICI, regions with higher complexity are expected to receive fewer funds than regions engaged in simpler activities. This pattern is evident in Figures 12A and 13A. It is further supported by the findings presented in Figure 8 in methodology, which highlight a strong correlation between a region's RICI level and its industrial ability to attract cohesion funds (IRFC).

Over the analysis period from 2010 to 2019, Figure 12D suggests that less developed and transition regions improved their RICI rankings, while more developed regions shared a slight decline. However, this direction represents an average, and Figure 13D complements the visualization that reveals significant variation within each group. The wide dispersion in ranking evolution suggests that it is not uniformly evident that less developed regions are becoming more complex, and so that funds help simpler regions jump into more complex activities.

To complement the regional analysis and bridge it to activity complexity, the correlation between relatedness density and the Industrial Complexity Index (ICI) was calculated. This analysis was compared with the Regional Industrial Complexity Index (RICI), as already illustrated in Figure 10 of the methodology, and the Industrial Regional Fund Capture (IRFC) to assess how these relationships influence each region's capacity to secure cohesion funds. Figure 14 A and B visualizes this relationship across the three categories of regional classifications.

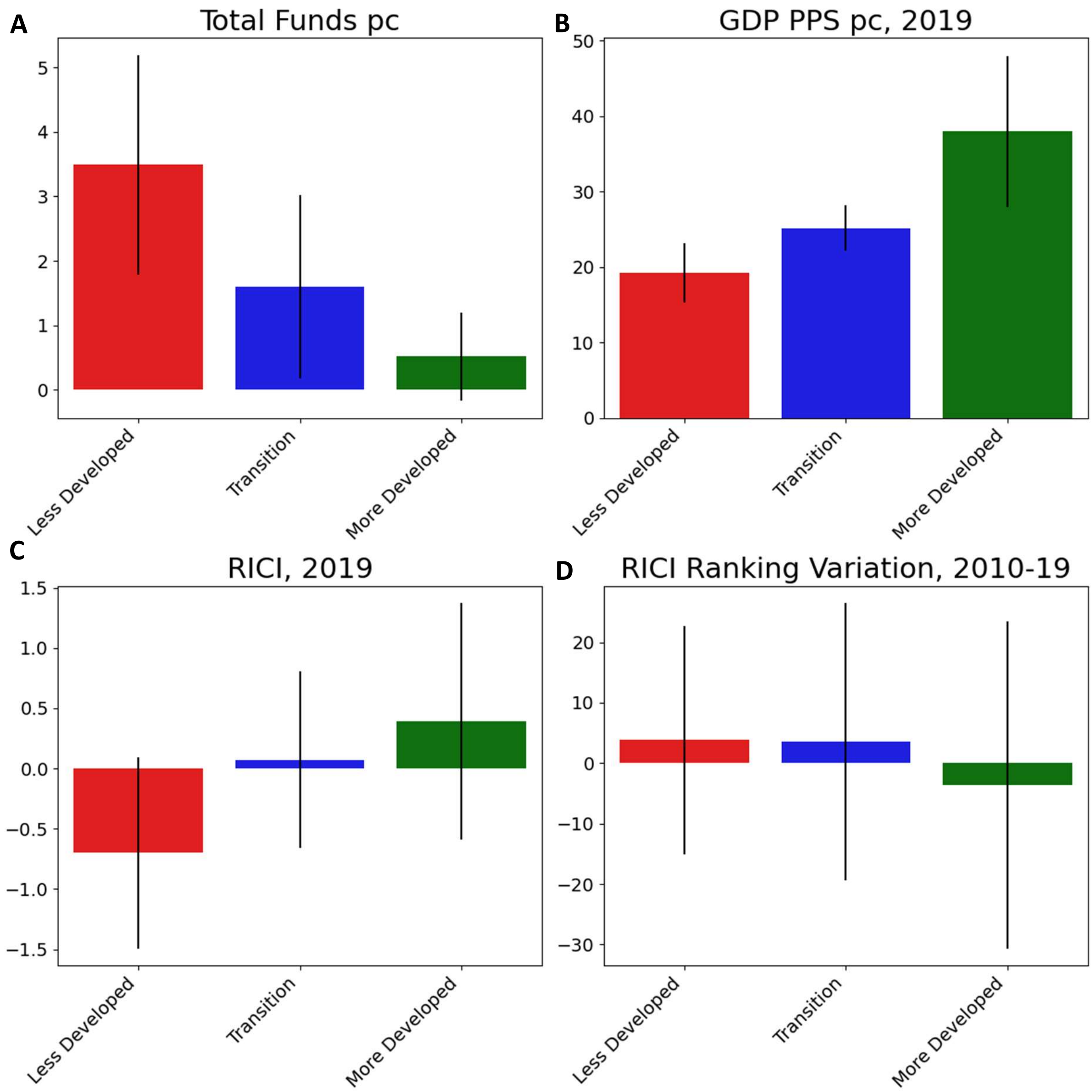

Figure 12 - For each eligible classification region, less developed (red), transition (blue), and more developed (green): **A.** Total ERDF, ESF, and Cf Funds expenditures related to 2007-13 and 2014-20 programs, in thousands. **B.** GDP PPS pc, for 2019, in thousands. **C.** Regional Industrial Complexity Index (RICI), for 2019. **D.** RICI Ranking evolution between 2010 and 2019.

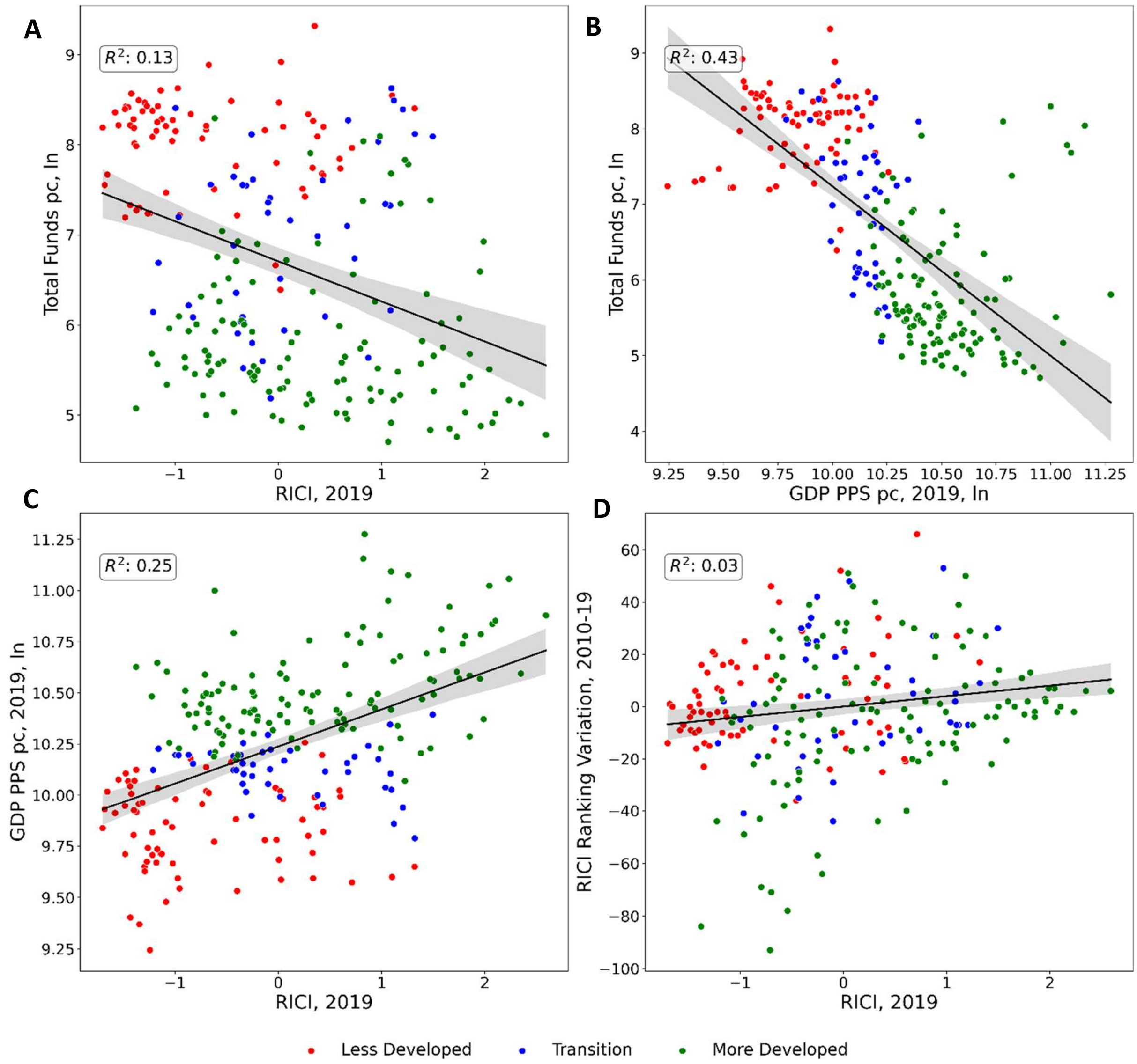

Figure 13 - Correlation between **A.** RICI, 2019, and the total expenditure ERDF, ESF, and Cf Funds related to 2007-13 and 2014-20 programs. **B.** GDP PPS pc (logarithm scale), 2019 and total expenditure ERDF, ESF, and Cf Funds related to 2007-13 and 2014-20 programs **C**. RICI and GDP PPS pc (logarithm scale), 2019. **D.** RICI, 2019, and RICI Ranking evolution between 2010 and 2019. Colors by each eligible classification region, less developed (red), transition (blue), and more developed (green).

The correlation, as a function of RICI, reveals an S-shaped curve, showing a non-linear relationship that aligns with the notion that regions pass through distinct stages of economic development (Pinheiro, Balland, et al., 2022). A positive correlation coefficient indicates that a region is closer to complex activities, while a negative coefficient reflects proximity to simpler activities (Figure 14A).

The correlation as a function of IRFC shows an inverted S shape that is more spread but suggests that complexity and funds allocation might follow opposite trajectories. Higher complexity levels of activities and regions are related to less capability to capture funds (Figure 14B).

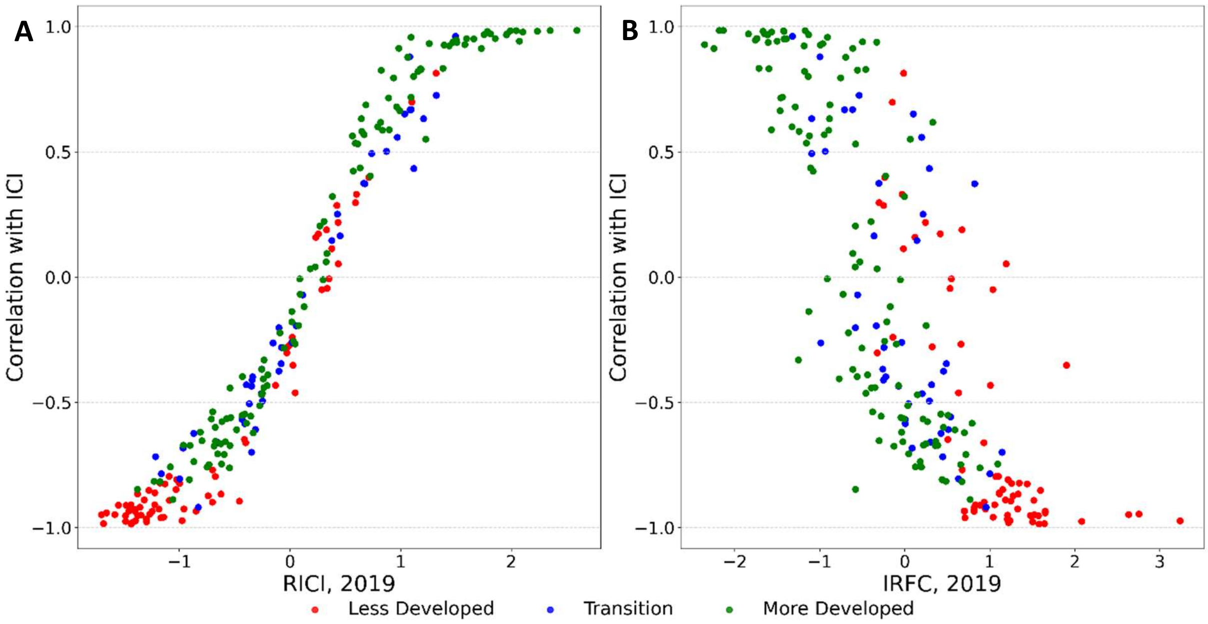

Figure 14 – **A**. Correlation between relatedness density and industrial complexity index (ICI) as a function of the Regional Industrial Complexity Index (RICI), 2019. **B**. Correlation between relatedness density and Industrial Complexity Index (ICI) as a function of the Industrial Region's Funds Capture (IRFC), 2019.

As regions advance in complexity, they evolve toward more sophisticated activities. Regions with high relatedness density in complex activities are better positioned to transition into new, high-complexity activities, thereby increasing their regional complexity. Figure 14A highlights that regions in this stage are predominantly more developed, distinguished by high complexity (RICI) and less reliance on or need for funds (low IRFC), as shown in Figure 14 B. A few less developed and transition regions are already in this stage or are passing in an intermediate stage.

In contrast, simpler regions usually remain trapped at the foundational level of their capabilities and knowledge, distant from complex activities and closer to simpler ones. These regions are primarily less developed and exhibit a high reliance on or more need for funds. Interestingly, some transition and even more developed regions display low levels of complexity, reinforcing the idea that GDP per capita may not fully capture the need for targeted investment in complexity-building activities to foster regional development.

This evidence stresses two critical concerns: whether cohesion funds are effectively targeted toward regions with more needs and whether these funds enable less developed regions to invest in high-complexity activities. On the one hand, GDP may be insufficient to target regions to receive funds. On the other hand, there are regions in need that have been receiving funds but continue to be trapped in developing low-complexity activities.

5.2. ACTIVITIES COMPLEXITY AND COHESION FUNDS

From an activity perspective, as summarized in the methodology section, activities with higher complexity typically require more advanced capabilities and specialized knowledge, resulting in only a few regions achieving comparative advantages in these fields. Examples include information and communication, as well as professional, scientific, and technical activities, as shown in Table 4. However, as demonstrated in Table 5, these complex activities exhibit a lower capacity to attract cohesion funds.

Conversely, simpler activities that demand less specialized knowledge tend to have comparative advantages across many regions. For example, manufacturing activities, highlighted in Table 4, are among those with the highest propensity to receive cohesion funds, as illustrated in Table 5. This dynamic explains the strong negative correlation between the Industrial Complexity Index (ICI) and the ability of Industrial Activities to Capture Funds (IAFC). In essence, the more complex an activity is, the less likely it is to attract funds, and vice versa, as shown in Figure 7.

To further investigate the interplay between funds and activities, a new analysis explored new entries and exits of activities by year, focusing on their complexity levels and the funds they received, categorized by region type: less developed, transition, and more developed. Figures 15 and 16 provide examples of these dynamics between 2018 and 2019, while additional yearly variations are detailed in Appendix B, Figures B1 and B2.

Despite the high variability and the different results in different years, Figure 15 reveals that, on average, between 2018 and 2019, less developed and transition regions see a higher influx of simpler activities and a more significant outflow of complex ones. A similar observation applies to the relation of entries and exits with funds. The mean IAFC of new activities is higher than those that exited for less developed and transition regions, as presented in Figure 16. This suggests that funds invest more in low-complex activities and incentivize more complex activities to exit, increasing the gap and decreasing the complexity.

It may be valuable to analyze specific success or failure cases within each regional classification to gain deeper insights into the influence of funds and complexity. Highlighting such examples could uncover positive and negative lessons, shedding light on how these two forces interact in different contexts. That will be discussed in the next section.

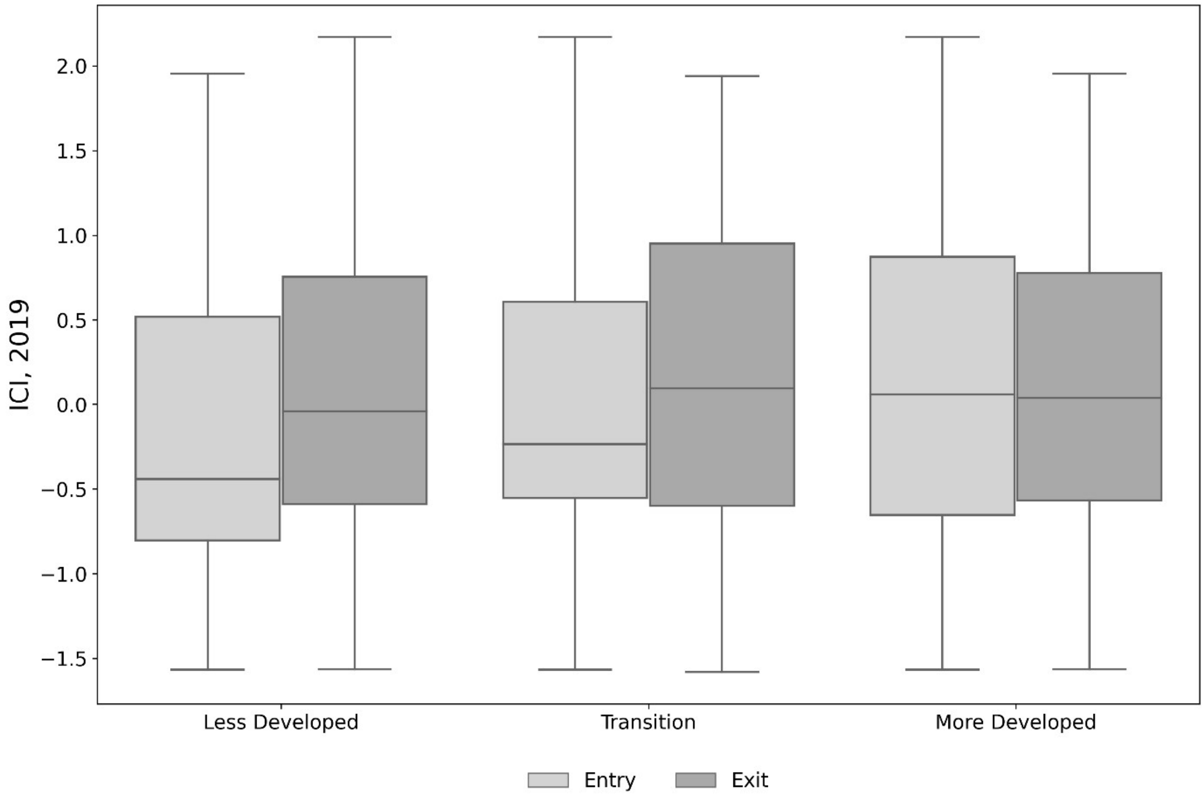

Figure 15 - Complexity level of new industrial activities entries and exits, split by eligible regions classification - less developed, transition, and more developed - between 2018 and 2019.

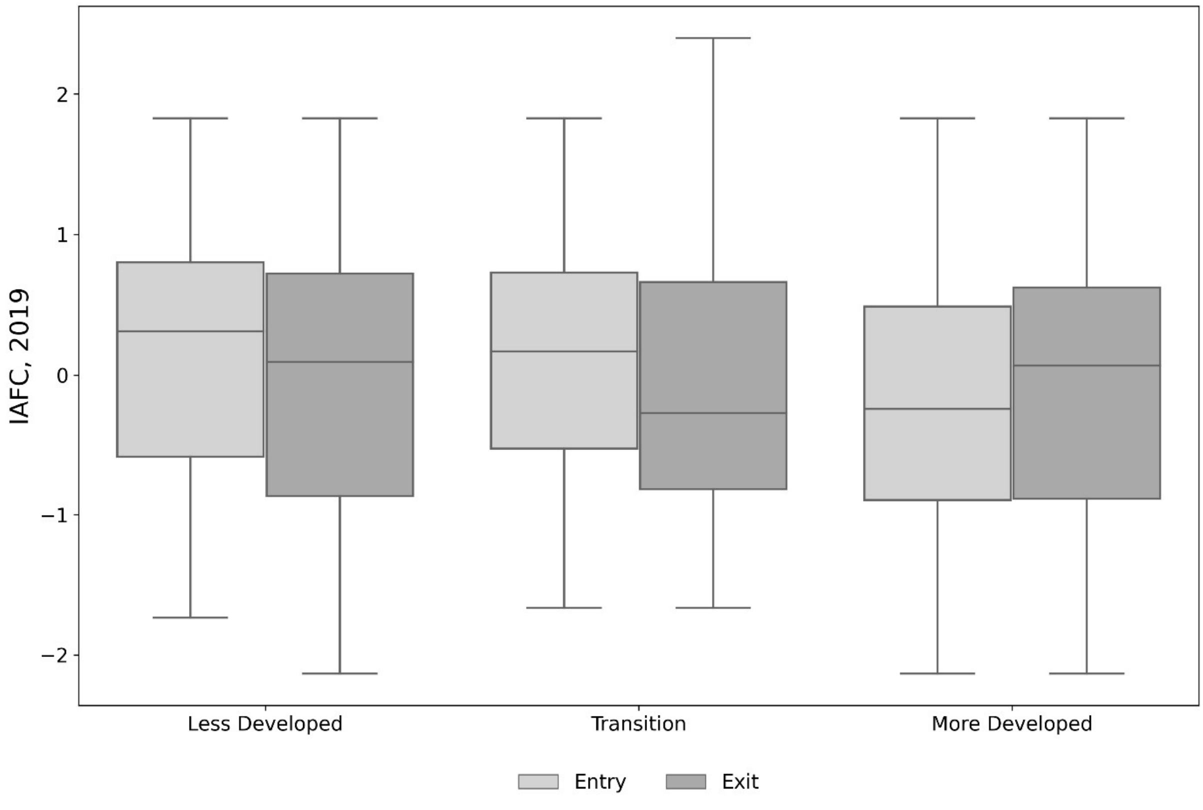

Figure 16 - Funds capture level of new industrial activities entries and exits, split by eligible regions classification - less developed, transition, and more developed - between 2018 and 2019.

5.3. THE IMPACT ON ECONOMIC GROWTH

For the 231 NUTS-2 regions in the European Union, during the period spanning the two most recently completed programs, the annual GDP PPS per capita increased by 2.46% between 2007, the first year of the 2007-2013 program, and 2022, the final year of expenditures for the 2014-2020 program, as shown in Figure 17. Less developed regions exhibited the highest growth, with an annual GDP PPS per capita increase of 3.47%, catching up with transition regions (1.82%) and more developed regions (2.01%). This indicates the presence of β-convergence, where less-developed regions grow faster than more developed regions. However, transition regions experienced relatively slower growth than less developed and more developed regions.

From the GDP PPS per capita standard deviation perspective in logarithmic terms, the aggregate values for all regions showed a total decline, reflecting α-convergence among the 231 NUTS-2 regions. However, this convergence appears to be driven primarily by the less developed regions, whose GDP PPS per capita (logarithmic scale) also dropped during this period. In contrast, the GDP PPS per capita values appear to be more spread distributed for transition and more developed regions, indicating high disparities within these groups.

This analysis can also be extended to different time frames, such as:

- **2007-2015**, covering the expenditure period of the first program,
- **2014-2022**, the expenditure period of the second program, or
- **2010-2019**, corresponding to the occupational period analysis.

As shown in Appendix E, Figure E1, the conclusions remain consistent across these periods.

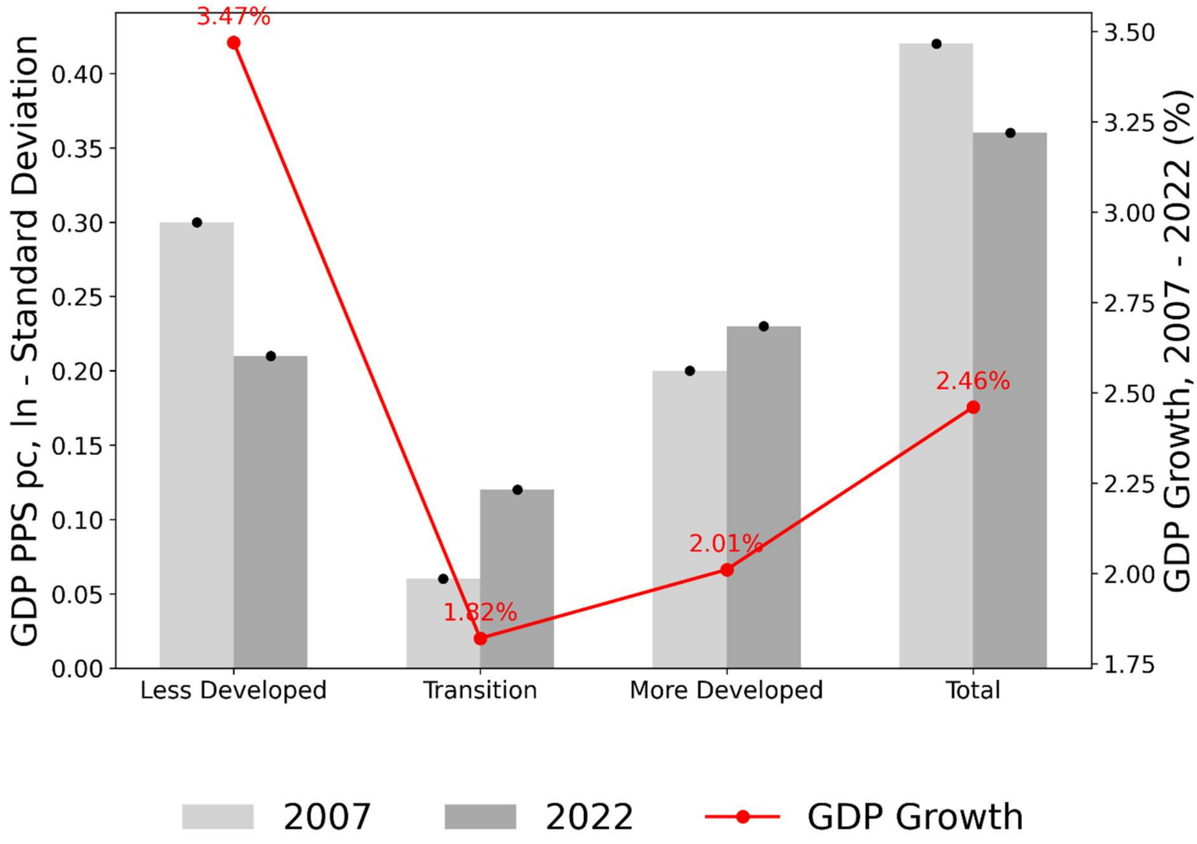

Figure 17 - Standard deviation of GDP PPS pc (logarithm scale) for 2007 and 2022 and the annual GDP Growth between 2007 and 2022 for each eligible classification region - less developed, transition, more developed - for the total 231 NUTS 2 regions.

As shown in Figure 18, additional understanding can be attained into each region's GDP growth and its relationship with key variables such as GDP PPS per capita, total fund expenditures, regional complexity levels, and their evolution. There is a trend toward lower-income regions growing faster, as illustrated in Figure 18A. However, this trend is driven by some specific less developed regions. This same group of regions also received higher funding levels, as evident in Figure 18B. Regions with faster growth rates typically belong to the less developed category and are characterized by lower complexity levels. However, the evolution of regional complexity, measured by the ranking of RICI, over the analyzed period appears less consistent and does not show a clear trend.

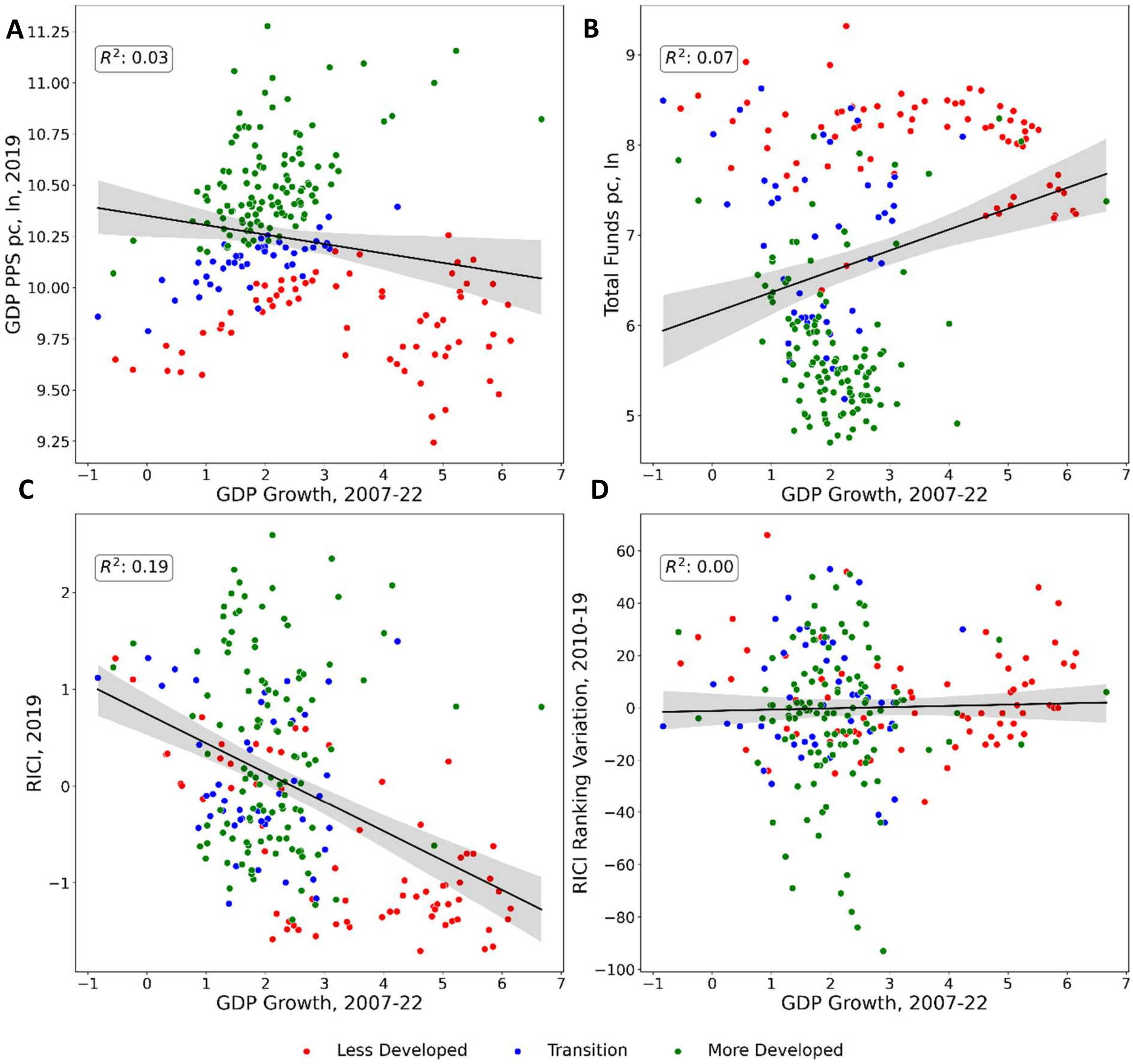

Figure 18 - Correlation of the annual GDP PPs pc growth between 2007 and 2022 and **A.** GDP PPS pc (logarithm scale), 2019 **B.** The total expenditure of ERDF, ESF, and Cf Funds related to 2007-13 and 2014-20 programs. **C.** RICI, 2019 **D.** RICI Ranking evolution between 2010 and 2019. Colors by each eligible classification region, less developed (red), transition (blue), and more developed (green).

Regions with lower GDP PPS per capita, higher fund absorption, and lower complexity grow faster. However, there are both strong and weak performers within each eligibility group - less developed, transition, and more developed regions. Using the smart specialization framework, six case studies will be explored to better understand how relatedness, complexity, and the capability to capture funds interact and influence regional success or failure: two regions from each group, highlighting strong and weak performance examples. This analysis evaluates each region's activity portfolio, categorizing activities throughout the RCA mean from the period in the analysis as the initial set of industrial activities (RCA = 1), new entries (0<RCA<1), exits (RCA < 0), and remaining potential new industrial activities (RCA = 0). The average relatedness is highlighted when RCA = o and the complexity when RCA = 1.

Case Studies for Less Developed Regions

Table 7 – Economic Growth and Complexity Performance for two less developed regions, Dolnośląskie (PL51) and Réunion (FR94)

	GDP Growth (2007-22)	RICI 2010	RICI 2019	RICI Ranking Growth	Funds pc (2007-22)
Dolnośląskie	5.52%	-1.45	-0.7	46	3,524
Réunion	2.07%	0.73	0.38	-25	3,270

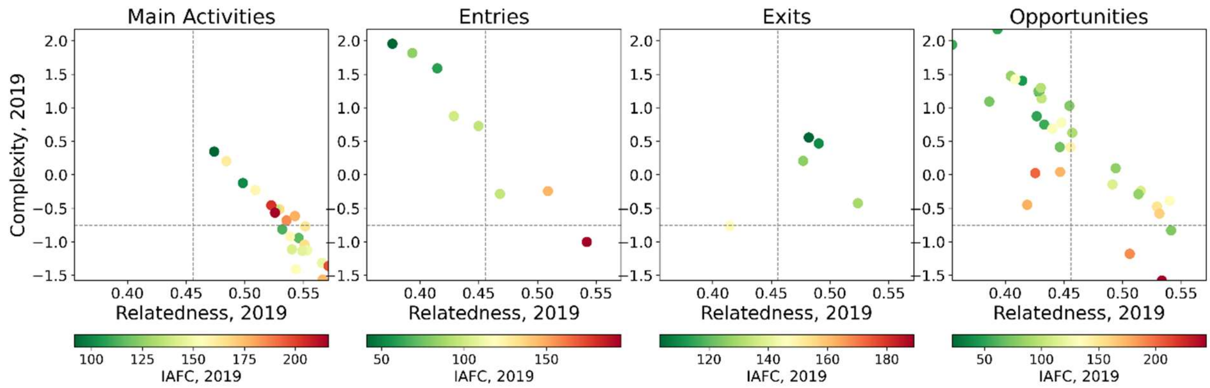

Figure 19 - 2019 complexity, relatedness, and capability to raise funds, for main activities, new entries, exits, and open activities opportunities for Dolnośląskie (PL51).

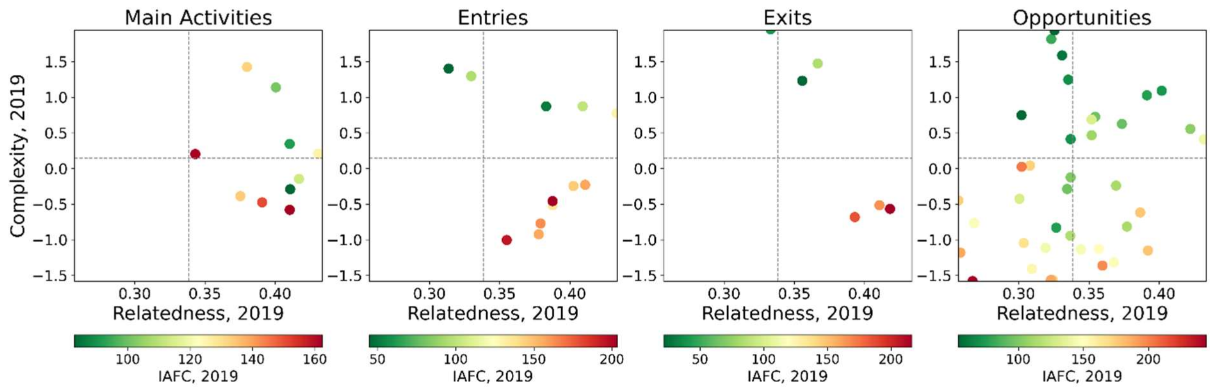

Figure 20 - 2019 complexity, relatedness, and capability to raise funds, for main activities, new entries, exits, and open activities opportunities for Réunion (FR94)

In 2010, Dolnośląskie and Réunion, classified as less developed regions, displayed contrasting economic and complexity trends over the analysis period.

Dolnośląskie established good economic progress, with an annual GDP Growth of 5.52%, over this region's average (3.47%). It was a region with a low complexity RICI of -1.45 in 2010, and despite still belonging to a low complexity region in 2019, with a RICI of -0,7, it increased in ranking by 46 positions (Table 7).

In contrast, Réunion underperformed economically, with a GDP growth of only 2.07%, below the region's average (3.47%). With an initial high complexity (RICI of 0.73), Réunion's complexity declined, losing 25 positions in the ECI ranking and a low RICI of -0.7 by 2019 (Table 7).

Figure 19 analysis reveals that Dolnośląskie's core activities, with a consistent RCA of 1 throughout the analysis period, were generally low in complexity. However, the region strategically diversified its economic profile. It invested in activities with high IAFC (Industries with more capability to raise funds), high relatedness, and low complexity, and in activities with low IAFC (Industries with fewer funds capability), low relatedness but high complexity. Despite the market having lost some activities with intermediate complexity, introducing new high-complexity sectors has brought a more complex profile.

In Réunion, however, core activities were generally of intermediate to high complexity. Over time, the region diversified by investing in low-complexity sectors, high relatedness, named ‘slow road’, with high IAFC (industries able to attract significant funding) but in a few high-complexity sectors with low IAFC. Additionally, the region experienced an outflow of activities with a higher average complexity than new entrants, as shown in Figure 20, resulting in an overall decline in regional complexity that might explain the slower economic growth.

Looking forward, both Dolnośląskie and Réunion have the potential to increase the complexity level; both have opportunities called the “high road” of smart specialization framework, with high complexity and relatedness. However, strategic shifts are necessary to realize this potential, mainly for Réunion. Dolnośląskie can benefit from focusing on activities with high relatedness and intermediate complexity to continue their good economic and complexity performance. Similarly, Réunion shows promise, with many opportunities in high-complexity and high-relatedness sectors. To strengthen Réunion's complexity profile, a strategic shift towards higher-complexity investments is crucial.

Case Studies for Transition Regions

Table 8 - Economic Growth and Complexity Performance for two transition regions - Malta (MT00) and Región de Murcia (ES62).

	GDP Growth (2007-22)	RICI 2010	RICI 2019	RICI Ranking Growth	Funds pc (2007-22)
Malta	4.23%	0.78	1.50	30	3,266
Región de Murcia	1.00%	0.31	-0.10	-29	1,572

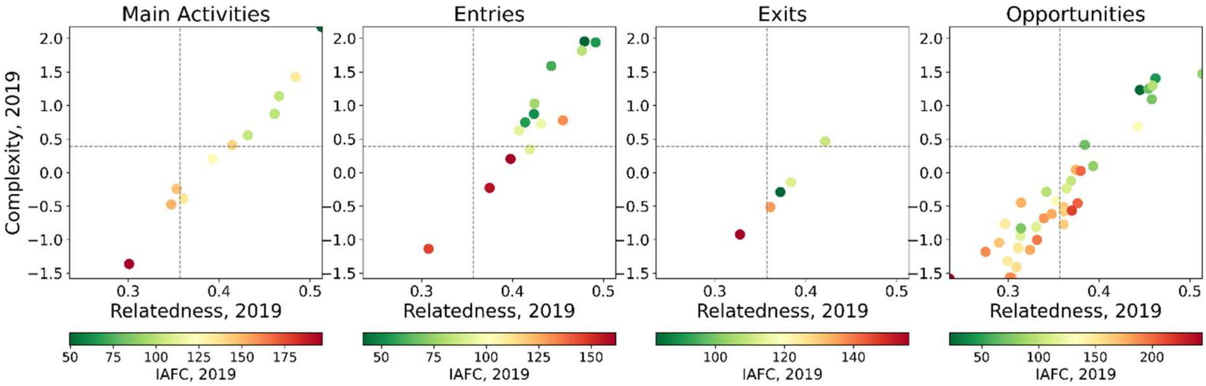

Figure 21 - 2019 complexity, relatedness, and capability to raise funds, for main activities, new entries, exits, and open activities opportunities for Malta (MT00).

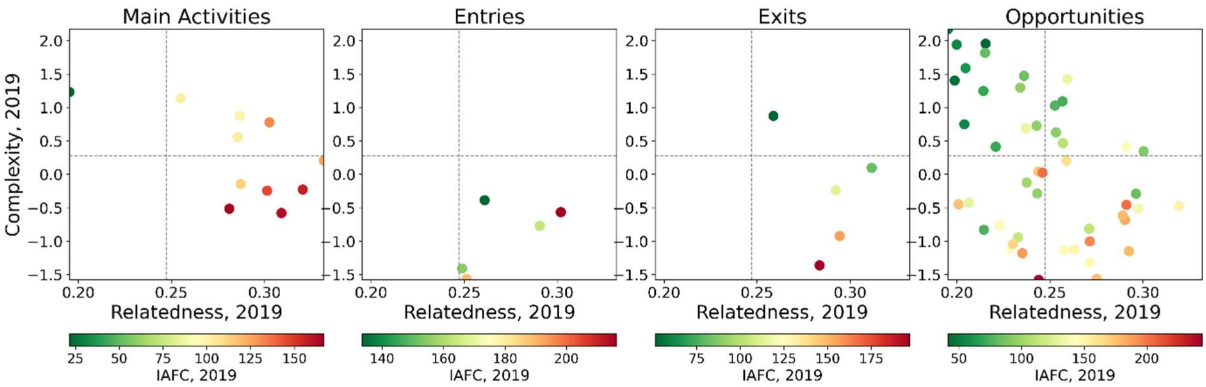

Figure 22 - 2019 complexity, relatedness, and capability to raise funds, for main activities, new entries, exits, and open activities opportunities for Región de Murcia (ES62).

Two contrasting cases are presented for the transition regions: Malta, with solid performance, and Región de Murcia, with weaker economic results.

As presented in Table 8, Malta experienced an annual GDP growth above the regional average, at 4.23%, compared to the average of 1.82%. Already set with a comparative advantage in complex activities in 2010, Malta had a RICI score 0.78. Over the period up to 2019, many new activities entered, most of which were highly complex and related ("high road"), with only a few exits of activities and with less complexity (Figure 21). By 2019, Malta's complexity had increased, moving it up 30 positions in the RICI ranking to a score of 1.5. In the future, Malta will have additional opportunities for complex activities with high relatedness. While these activities present a low IAFC, they are a strategic target for reallocating policy funds to support continued growth.

On the other hand, Región de Murcia, also classified as a Transition region, had an annual GDP growth of just 1%, below the average of 1.82%. Starting with a positive RICI of 0.31 in 2010, indicating an intermediate complexity level, Murcia fell 29 in the RICI ranking, ending with a RICI score of -0.09 in 2019 (Table 8). Figure 22 shows a few new investments. The new entries had low complexity and fund levels. At the same time, Murcia saw a higher rate of exits, some of which were relatively high in complexity. Nevertheless, Murcia still has substantial opportunities across all quadrants of the smart specialization framework. Although the region has fewer options in the quadrant with high complexity and relatedness, this area could be an important next step in advancing Murcia's economic complexity.

Case Studies for More Developed Regions

Table 9 - Economic Growth and Complexity Performance for two more developed regions - Zahodna Slovenija (SI02) and Lazio (ITI4).

	GDP Growth (2007-22)	RICI 2010	RICI 2019	RICI Ranking Growth	Funds pc (2007-22)
Zahodna Slovenija	2.33%	-0.19	0.31	40	2,716
Lazio	0.85%	1.42	1.39	-4	337

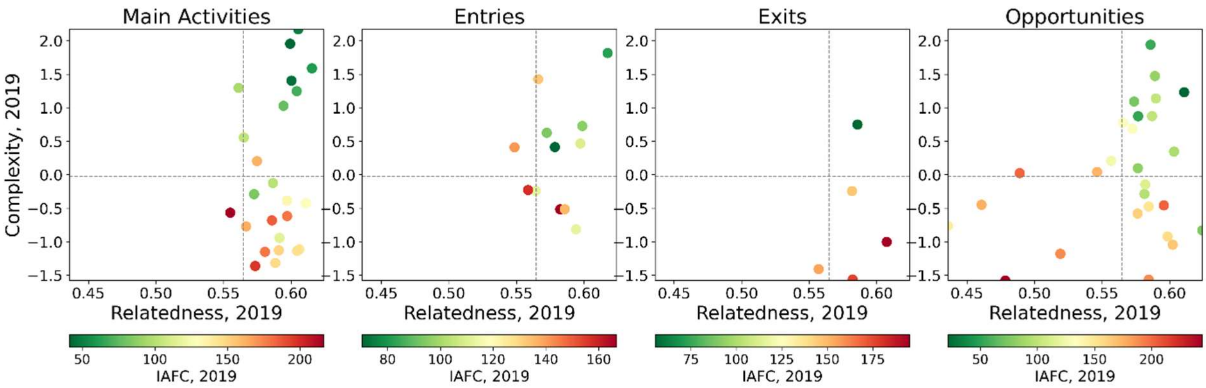

Figure 23 - 2019 complexity, relatedness, and capability to raise funds, for main activities, new entries, exits, and open activities opportunities for Zahodna Slovenija (SI02).

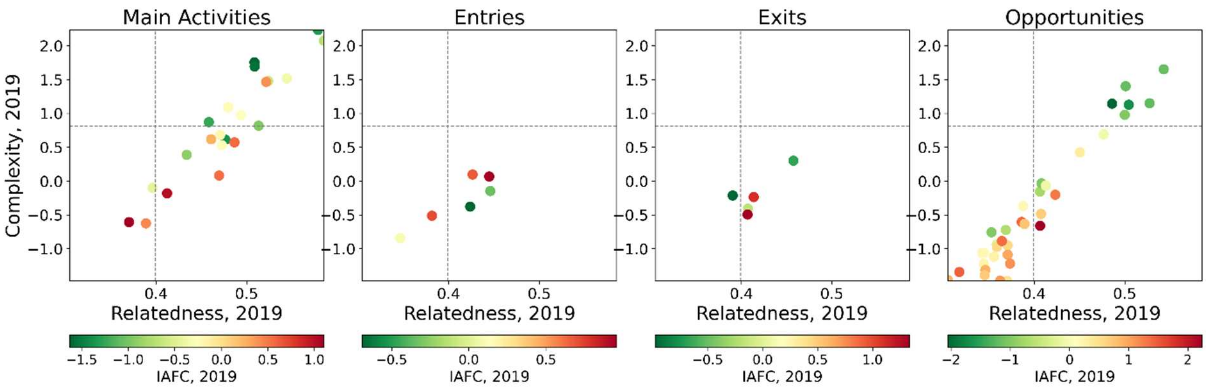

Figure 24 - 2019 complexity, relatedness, and capability to raise funds, for main activities, new entries, exits, and open activities opportunities for Lazio (ITI4).

Zahodna Slovenija encountered an annual GDP growth above the regional average, at 2.33%, compared to 2.01%. This region in 2010 was in the intermediate complexity stage with a RICI score of -0.19 (Table 9). Over the period up to 2019, many new activities entered, most of which were highly complex and related, with both high and low IAFC (Figure 23). Some activities, despite the high level of capability to catch funds, exited the region, but as these activities had low levels of complexity, the region was able to increase its complexity level, growing in complexity by 40 positions in ranking, ending in 2019 with a RICI score of 0.31. This region still can have a promising horizon in the future, with many opportunities to grow in more complex activities and high relatedness.

As for Lazio, it was a region that grew under the average of the more developed region's group, with 0.85% against 2.01%. This region already had a high level of complexity, with a RICI score of 1.42 in 2010 (Table 9). During 2010-2019, there were some entries and exits with an intermediate and low level of complexity. However, it was a strategic misstep in the diversity strategy, as shown in the opportunity's activities, this region has many activities that can enter with high levels of relatedness and complexity, as shown in Figure 24.

Our case studies and previous analyses reveal a correlation between a diversification strategy and high economic performance in regions. Regions that invest in higher-complexity activities tend to experience greater economic growth. In this diversification process, these case studies point out that relatedness may be more influential than cohesion funds, which predominantly invest in simpler activities.

These case studies underscore the role of a smart specialization framework in regional cohesion policy. This framework is important in guiding the selection of paths that enhance comparative advantages in more complex knowledge, thereby fostering European economic convergence, high performance, and improved competition.

6. CONCLUSIONS AND FUTURE WORKS

6.1. CONCLUSION

Since the inception of the Treaty of Rome in 1957, the European Union (EU) has pursued the goal of reducing economic and social disparities among its regions. The introduction of cohesion in 1987, with its embedded principles of solidarity, concentration, and partnership, marked a significant step in this direction (Paolo et al., 2009). The EU's Cohesion Policy (CP) has evolved over time, experiencing continuous reforms, primarily due to new integrations. Cohesion has become synonymous with the concept of convergence, a process that can be measured by β-convergence or α-convergence. This implies that less developed regions grow faster than more developed regions, thereby reducing regional disparities, a process measured by GDP per capita and their growth (Marinas et al., 2023).

The EU has relied on the European Structural and Investment Funds (ESIF) to achieve this convergence, particularly the ERDF, ESF, and CF. Since 1999, these funds have been viewed as investments rather than mere acts of solidarity. The 2007-2013 programming period focused on competitiveness by fostering knowledge, research, and technological development. This focus was reinforced during the 2014-2020 period, and polycentric regional development was added to increase other economies of scale across territories to avoid the existing clusters. The 2014-2020 period also introduced the smart specialization strategy, which is a regional development concept that aims to identify and develop a region's unique strengths and competitive advantages.

This analysis splits the European Union into three regions according to the eligibility criterion: less developed, transition, and more developed. Overall, there is β-convergence and α-convergence, with less-developed regions catching up with more-developed regions. Less developed regions have less initial GDP PPS per capita, receive more funds, are less complex, and grow fast. More developed regions, with high initial GDP PPS per capita, receive less funds, are more complex, and grow slower.

Economic diversification, especially into more complex activities, can be a strategic path for reducing economic risk and improving income. However, achieving this requires structural transformation, which involves expanding the variety and sophistication of economics (Felipe et al., 2012).

European funds should be a valuable instrument for achieving this goal. However, this study suggests that these investments have been implemented mainly in industrial activities with a low level of complexity, avoiding or delaying the structural transformations needed to increase the complexity level in less developed regions.

Some studies reveal that for such transformations to occur, different factors must be considered, such as institutional reforms (Mokyn, 1992), modern management practices (Chandler, 1994), contemporary research and development efforts (Freeman & Soete, 1997), and appropriate educational systems (Goldin & Katz, 2009).

It needs to be clarified how cohesion funds influence the entry and exit of new industrial activities, but as the case studies show, some regions have better strategies than others. In the cases of success, investing in highly complex new activities was key to economic growth.

Despite some unsuccessful cases, the smart strategy framework has revealed a high potential for growth in all regions. With the right strategies, these regions can shift their productive structures and experience the necessary structural change. They can retain a comparative advantage in simple activities and continue investing in and modernizing them. However, with the proper support and guidance, these regions can advance to more complex activities, paving the way for sustainable growth, fostering economic growth, improving competitiveness, and European economic convergence.

6.2. LIMITATIONS AND FUTURE WORK

Some limitations encountered during this analysis can be an opportunity for future research:

Data Availability: The dataset on regional occupation covers fewer years than the cohesion programs analyzed. Future studies could focus on completed programs for better results validation when more data is available.

Upcoming Programming Period (2020-2027): As data from the current programming period becomes available, it will be interesting to examine how funds are allocated and their relationship to regional and activity complexity, particularly regarding entry and exit patterns as the idea of smart specialization for research and innovation was reinforced and updated.

Impact Analysis: Regression analyses could provide deeper insights into how the level of the fund's capture capabilities influence the entry and exit of new activities or even the region's convergence.

Patent Data: Patent data was analyzed (Appendix F), and despite the opportunity to have data that covers the two last programs, the data revealed noise and divergent patterns compared to occupation data. Further exploration is needed to understand these differences and their implications.

Future research should also examine how cohesion funds can support innovation and specialization strategies more effectively, ensuring their alignment with long-term regional development goals. By addressing these challenges, policymakers can refine cohesion policies to better balance economic performance and convergence across EU regions.

7. BIBLIOGRAPHICAL REFERENCES

Aghion, P., & Howitt, P. (1990). *A model of growth through creative destruction* (3223; NBER Working Paper Series).

Asheim, B. T., & Gertler, M. S. (2005). The Geography of Innovation: Regional Innovation Systems. In *The Oxford Handbook of Innovation*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199286805.003.0011

Audretsch, D. B., & Feldman, M. P. (1996). Spillovers and the geography of innovation and production. *The American Economic Review*, *86,3*, 630.

Autant-bernard, C., Billand, P., Frachisse, D., & Massard, N. (2007). Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaboration choices in micro and nanotechnologies. *Papers in Regional Science*, *86*(3), 495–519. https://doi.org/10.1111/j.1435-5957.2007.00132.x

Balassa, B. (1965). *Trade Liberalisation and Revealed Comparative Advantage* (Vol. 33). The Manchester School.

Baldwin, R., Forslid, R., Martin, P., Ottaviano, G., Robert-Nicoud, F., & Neary, J. P. (2003). *Economic Geography & Public Policy*. Princeton University Press.

Balland, P., Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, *53*(9), 1252–1268. https://doi.org/10.1080/00343404.2018.1437900

Balland, P., Jara-Figueroa, C., Petralia, S., Steijn, M., Rigby, D., & Hidalgo, C. A. (2020). *Complex Economic Activities Concentrate in Large Cities*.

Balland, P., & Rigby, D. (2017). The Geography of Complex Knowledge. *Economic Geography*, *93*(1), 1–23. https://doi.org/10.1080/00130095.2016.1205947

Becker, S. O., Egger, P. H., & Ehrlich, M. Von. (2013). Absorptive capacity and the growth and investment effects of regional transfers: A regression discontinuity design with heterogeneous treatment effects. *American Economic Journal: Economic Policy*, *5*(4), 29–77. https://doi.org/10.1257/pol.5.4.29

Becker, S. O., Egger, P. H., & von Ehrlich, M. (2018). Effects of EU Regional Policy: 1989-2013. *Regional Science and Urban Economics*, *69*, 143–152. https://doi.org/10.1016/j.regsciurbeco.2017.12.001

Boldrin, M., & Canova, F. (2001). Inequality and convergence in Europe's regions: Reconsidering European regional policies. *Economic Policy*, *32*, 205–253. https://doi.org/10.1111/1468-0327.00074

Boschma, R. (2014). Constructing Regional Advantage and Smart Specialization: Comparison of Two European Policy Concepts. *Papers in Evolutionary Economic Geography*, *13.22*. http://econ.geog.uu.nl/peeg/peeg.html

Boschma, R., Balland, P. A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, *24*(1), 223–250. https://doi.org/10.1093/icc/dtu012

Boschma, R., Minondo, A., & Navarro, M. (2013). The Emergence of New Industries at the Regional Level in Spain: A Proximity Approach Based on Product Relatedness. *Economic Geography*, *89*(1), 29–51. https://doi.org/10.1111/j.1944-8287.2012.01170.x

Brandsma, Andries., Montfort, Philippe., Kancs, d'Artis., & Rillaers, Alexandra. (2013). *Rhomolo, a dynamic spatial general equilibrium model for assessing the impact of cohesion policy*. Publications Office.

Cappelen, A., Castellacci, F., Fagerberg, J., & Verspagen, B. (2003). The Impact of EU Regional Support on Growth and Convergence in the European Union. *Journal of Common Market Studies*, *41*(4), 621–644. https://doi.org/10.1111/1468-5965.00438

Cerqua, A., & Pellegrini, G. (2018). Are we spending too much to grow? The case of Structural Funds. *Journal of Regional Science*, *58*(3), 535–563. https://doi.org/10.1111/jors.12365

Constantin, D. L., Dragan, G., Goschin, Z., Radu, L. N., Constantin, D., Dragan, G., Goschin, Z., & Radu, L. (2010). Implications of the latest enlargement on regional disparities and cohesion policy. A spotlight on the EU funds absorption. *50th Congress of the European Regional Science Association: "Sustainable Regional Growth and Development in the Creative Knowledge Economy."* https://hdl.handle.net/10419/119134

Crescenzi, R., & Giua, M. (2016). The EU Cohesion Policy in context: Does a bottom-up approach work in all regions? *Environment and Planning A*, *48*(11), 2340–2357. https://doi.org/10.1177/0308518X16658291

Crescenzi, R., & Giua, M. (2018). One or Many Cohesion Policies of the European Union? On the Diverging Impacts of Cohesion Policy across Member States. *Spatial Economics Research Centre*.

Crucitti, F., Lazarou, N. J., Monfort, P., & Salotti, S. (2023). Where does the EU cohesion policy produce its benefits? A model analysis of the international spillovers generated by the policy. *Economic Systems*, *47*(3). https://doi.org/10.1016/j.ecosys.2023.101076

Di Caro, P., & Fratesi, U. (2022). One policy, different effects: Estimating the region-specific impacts of EU cohesion policy. *Journal of Regional Science*, *62*(1), 307–330. https://doi.org/10.1111/jors.12566

European Comission. (2023). *Cohesion 2021-2027: forging an ever stronger Union. Report on the outcome of 2021-2027 cohesion policy programming*.

European Commission. (2013). *Report from the commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions*. http://ec.europa.eu/europe2020/pdf/ags2013_en.pdf.

Feldman, M. P. (2016). Geography of Innovation. In *The Palgrave Encyclopedia of Strategic Management* (pp. 1–6). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-94848-2_537-1

Felipe, J., Kumar, U., Abdon, A., & Bacate, M. (2012). Product complexity and economic development. *Structural Change and Economic Dynamics*, *23*(1), 36–68. https://doi.org/10.1016/j.strueco.2011.08.003

Flam, H., & Flanders, J. M. (1991). *Heckscher-Ohlin Trade Theory*. MIT Press.

Fleming, L., & Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. In *Research Policy* (Vol. 30).

Gagliardi, L., & Percoco, M. (2017). The impact of European Cohesion Policy in urban and rural regions. *Regional Studies*, *51*(6), 857–868. https://doi.org/10.1080/00343404.2016.1179384

Hartmann, D., Bezerra, M., Lodolo, B., & Pinheiro, F. L. (2020). International trade, development traps, and the core-periphery structure of income inequality. *EconomiA*, *21*(2), 255–278. https://doi.org/10.1016/j.econ.2019.09.001

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes, A., & Yildirim, M. A. (2013). *The Atlas of Economic Complexity : Mapping Paths to Prosperity*. The MIT Press Open.

Hausmann, R., Kennedy, J. F., Hwang, J., & Rodrik, D. (2006). *What You Export Matters*.

Hidalgo, C. A., Balland, P. A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D. F., Morrison, A., Neffke, F., Rigby, D., Stern, S., Zheng, S., & Zhu, S. (2018). The Principle of Relatedness. In *Springer Proceedings in Complexity* (Vol. 0, pp. 451–457). Springer Science and Business Media B.V. https://doi.org/10.1007/978-3-319-96661-8_46

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences (PNAS)*, *106*(26). www.pnas.org/cgi/doi/10.1073/pnas.0900943106

Hidalgo, C., Klinger, B., Barabási, A., & Hausmann, R. (2007). *The Product Space Conditions the Development of Nations*.

Iammarino, S., Rodriguez-Pose, A., & Storper, M. (2018). Regional inequality in Europe: evidence, theory and policy implications. *Journal of Economic Geography*.

Kotzeva, M., Brandmüller, T., & Önnerfors, A. (2015). *Eurostat regional yearbook 2015*. Publications Office of the European Union.

Krugman, P. R. (1991). *First Nature, Second Nature and Metropolitan Location* (3740; National Bureau of Economic Research).

Marinas, L. E., Croitoru, I. M., Pacesila, M., Marinas, C. V., Prioteasa, E., Bratiloveanu, A., & Bratiloveanu, I. F. (2023). Managing continuos transformation and complexity of the European Union Cohesion Policy. The simplification chalenge. *Management Research and Pactice*, *15*(4).

Marinas, L. E., & Priotease, E. (2016). Spotlight on Factors Influencing the Absorption Rate of EU Funds in Romania. *Journal of Eastern Europe Research in Business and Economics*, 1–14. https://doi.org/10.5171/2016.500580

Maskell, P., & Malmberg, A. (1999). The competitiveness of firms and regions. “Ubiquitification” and the importance of localized learning. *European Urban and Regional Studies*, *6*(1), 9–25. https://doi.org/10.1177/096977649900600102

Maynou, L., Saez, M., Kyriacou, A., & Bacaria, J. (2016). The Impact of Structural and Cohesion Funds on Eurozone Convergence, 1990–2010. *Regional Studies*, *50*(7), 1127–1139. https://doi.org/10.1080/00343404.2014.965137

Meijers, E., Hoogerbrugge, M., & Cardoso, R. (2018). Beyond Polycentricity: Does Stronger Integration Between Cities in Polycentric Urban Regions Improve Performance? *Tijdschrift Voor Economische En Sociale Geografie*, *109*(1), 1–21. https://doi.org/10.1111/tesg.12292

Melecký, L. (2018). The main achievements of the eu structural funds 2007–2013 in the eu member states: Efficiency analysis of transport sector. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *13*(2), 285–306. https://doi.org/10.24136/eq.2018.015

Miron, D., & Holobiuc, A.-M. (2020). Multi-speed Europe? An Analysis of the Real Convergence within the European Union. *KnE Social Sciences*. https://doi.org/10.18502/kss.v4i1.5980

Mohl, P., & Hagen, T. (2008). *Which is the right dose of EU cohesion policy for economic growth?* (08–104; ZEW Discussion Papers).

Moreno, R., Paci, R., & Usai, S. (2005). Geographical and sectoral clusters of innovation in Europe. *Annals of Regional Science*, *39*(4), 715–739. https://doi.org/10.1007/s00168-005-0021-y

Oleš, T., & Hudcovský, M. (2024). Impact of Cohesion Funds on Convergence Club's Economic Growth. *Growth and Change*, *55*(4). https://doi.org/10.1111/grow.12739

Paolo, G., European, M., Luxembourg, I. B., & Mendez, C. (2009). *The turning points of EU Cohesion policy*.

Piketty, T. (2014). *Capital in the Twenty-First Century*. The Belknap Press of Harvard University Press.

Pinheiro, F. L., Balland, P. A., Boschma, R., & Hartmann, D. (2022). The dark side of the geography of innovation: relatedness, complexity and regional inequality in Europe. *Regional Studies*. https://doi.org/10.1080/00343404.2022.2106362

Pinheiro, F. L., Hartmann, D., Boschma, R., & Hidalgo, C. A. (2022). The time and frequency of unrelated diversification. *Research Policy*, *51*(8). https://doi.org/10.1016/j.respol.2021.104323

Pinho, C., Varum, C., & Antunes, M. (2015). *Under what conditions do Structural Funds play a significant role for European regional economic growth? Some evidence from recent panel data*.

Robert J. Barro and Xavier I. Sala-i-Martin. (2003). *Economic Growth*.

Rodríguez-Pose, A., & Fratesi, U. (2003). *Between development and social policies: the impact of European Structural Funds in Objective 1 regions* Between development and social policies: the impact of European Structural Funds in Objective 1 regions ** (28/2003; The EEG Working Papers Series).

Rodríguez-Pose, A., & Garcilazo, E. (2015). Quality of Government and the Returns of Investment: Examining the Impact of Cohesion Expenditure in European Regions. *Regional Studies*, *49*(8), 1274–1290. https://doi.org/10.1080/00343404.2015.1007933

Shumpeter J. A. (1943). *Capitalism, Socialism and Democracy* (Taylor & Francis e-Library, Ed.). George Allen & Unwin.

Vedrine, L., & Le Gallo, J. (2021). Does EU Cohesion Policy affect territorial inequalities and regional development? *EU Cohesion Policy and Spatial Governance : Territorial, Social and Economic Challenges, Edward Elgar Publishing,* 156–170.

8. APPENDIX A – CORRELATION BETWEEN MAIN INDICATORS

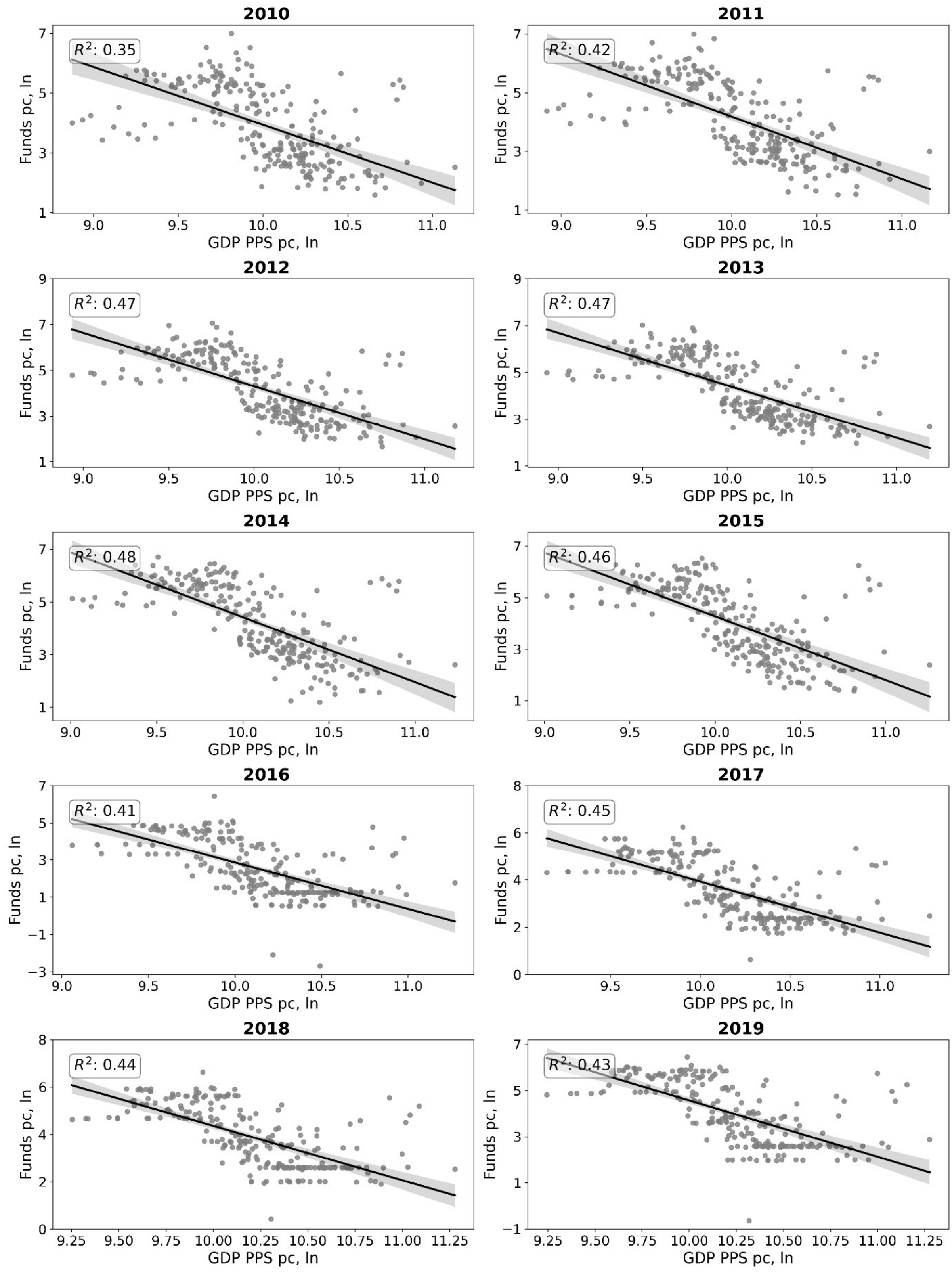

Figure A1 - GDP PPS per capita (logarithmic scale) and Funds (ERDF, ESF, and CF) expenditure per capita (logarithmic scale) correlation by year.

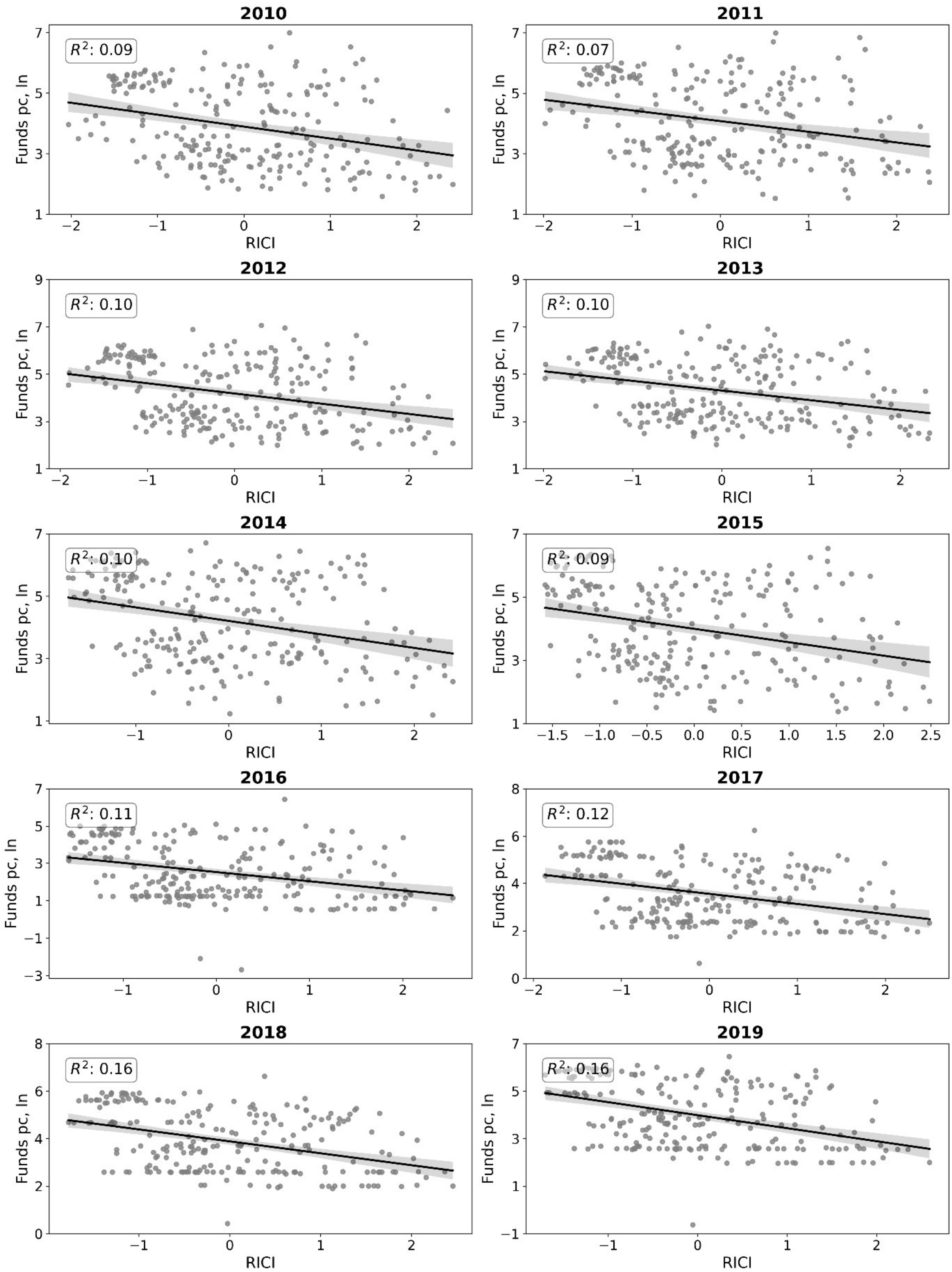

Figure A2 - RICI and Funds (ERDF, ESF, and CF) expenditure per capita (logarithmic scale) correlation by year.

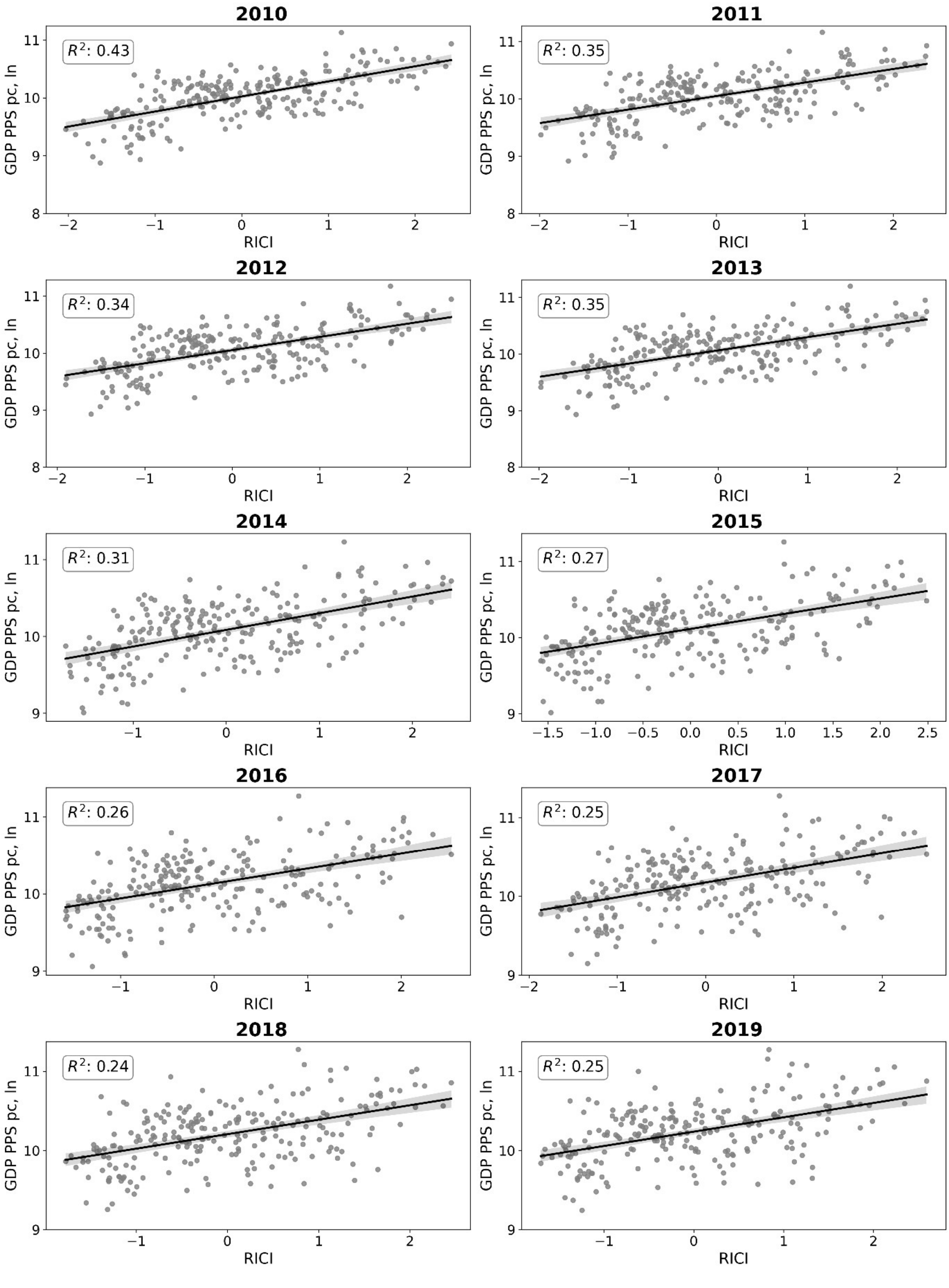

Figure A3 - RICI and GDP PPS per capita (logarithmic scale) correlation by year.

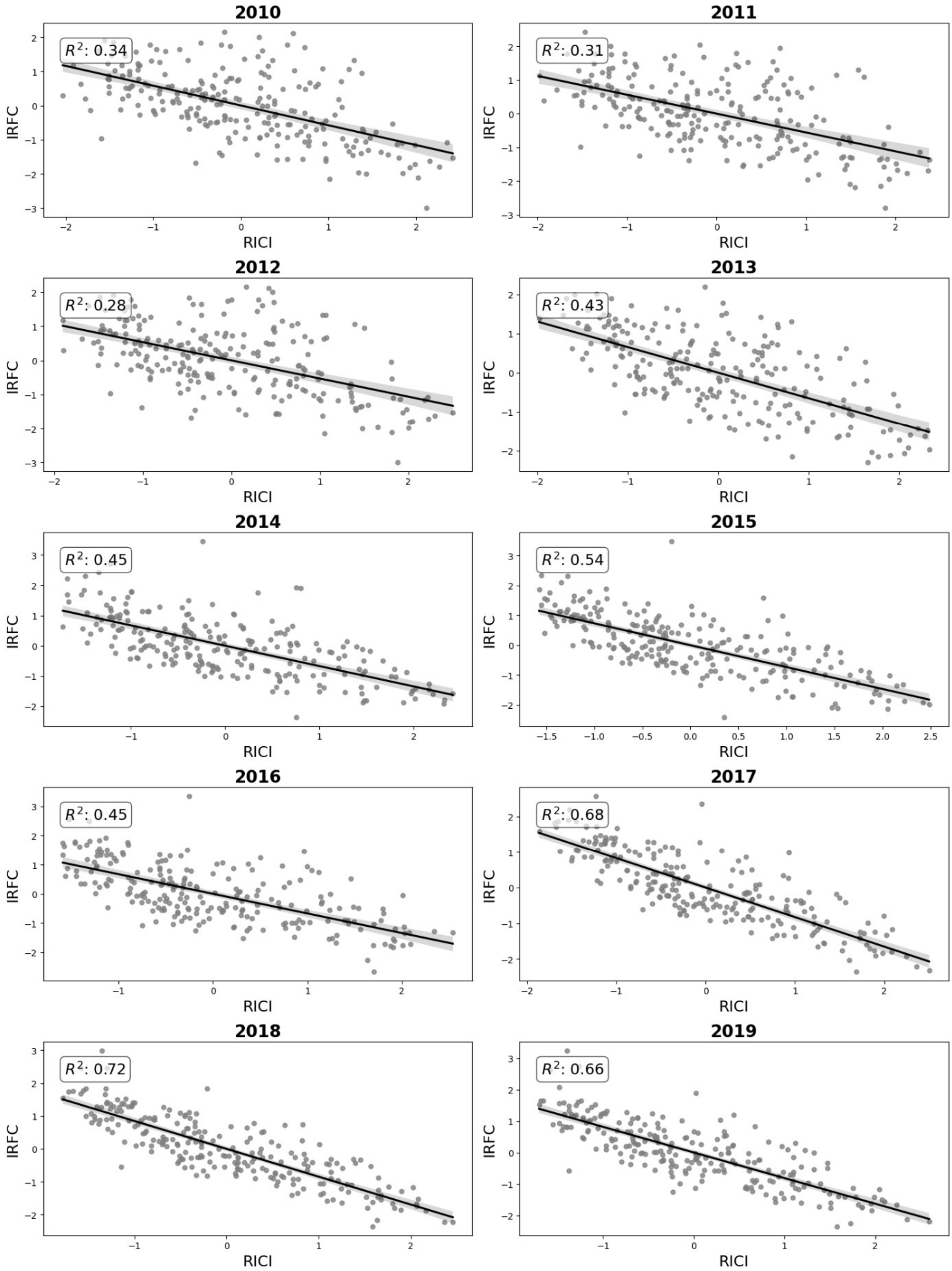

Figure A4 - RICI and IRFC correlation by year.

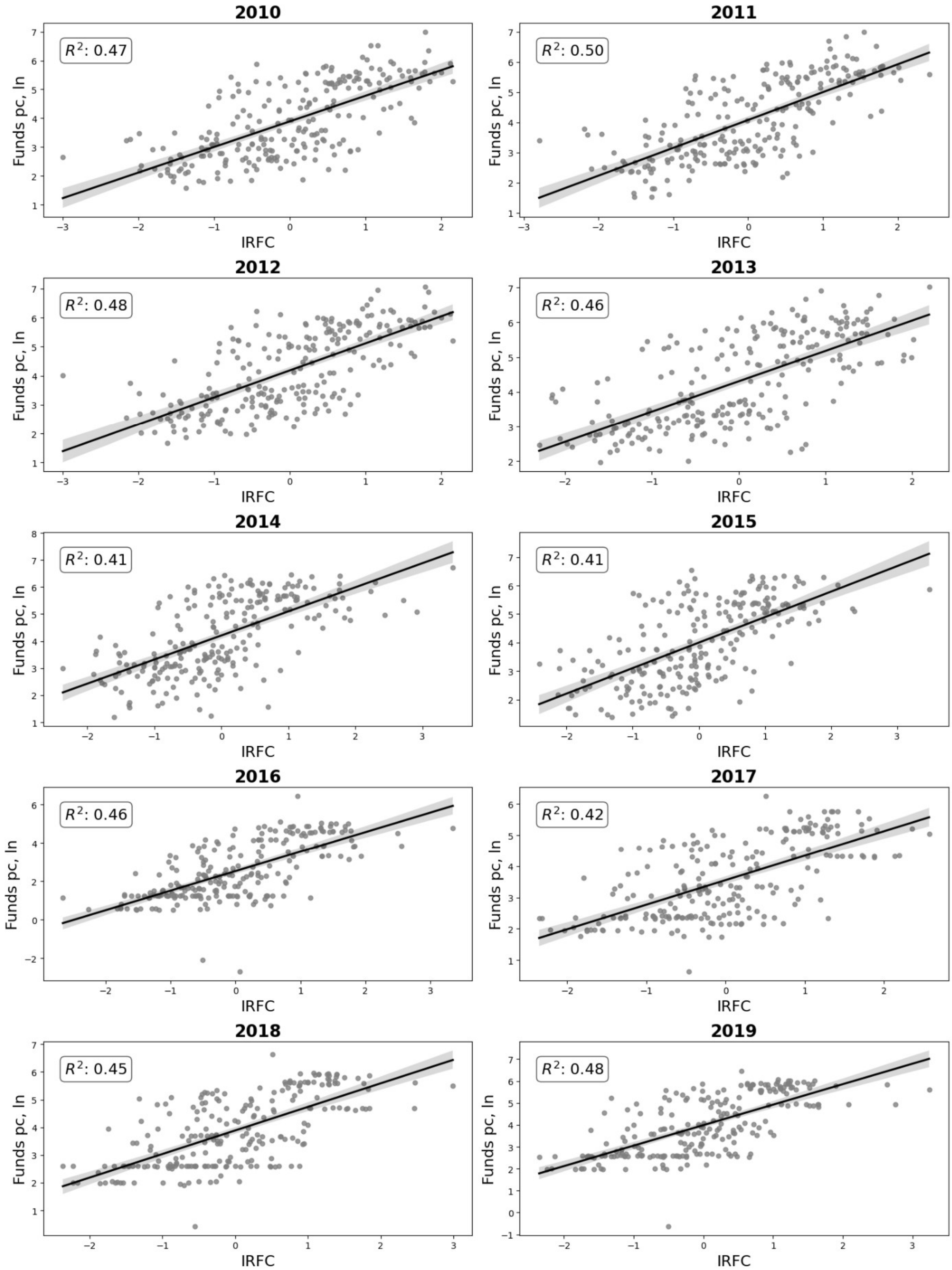

Figure A5 - IRFC and Funds (ERDF, ESF, and CF) expenditure per capita (logarithmic scale) correlation by year.

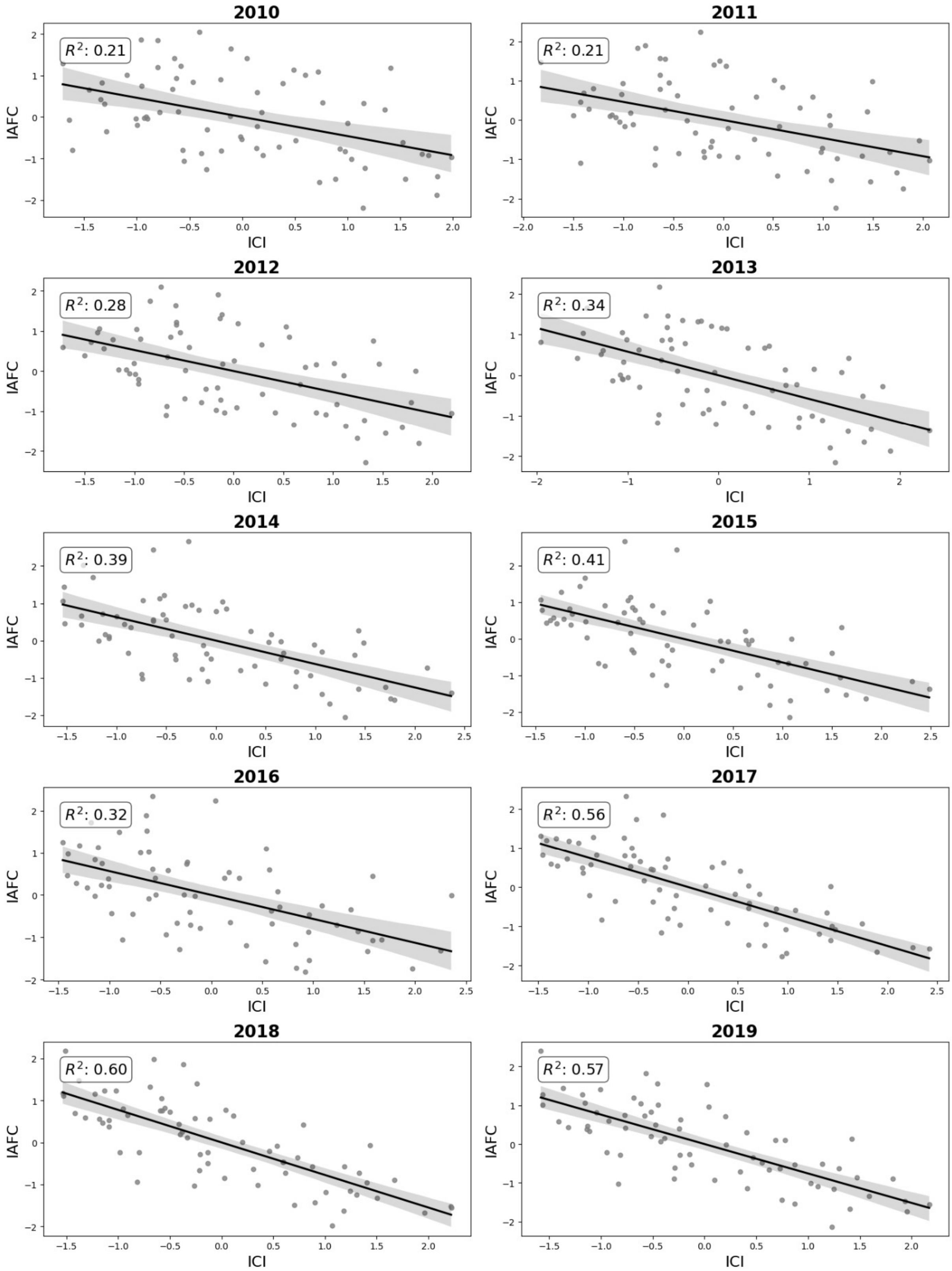

Figure A6 - ICI and IAFC correlation by year.

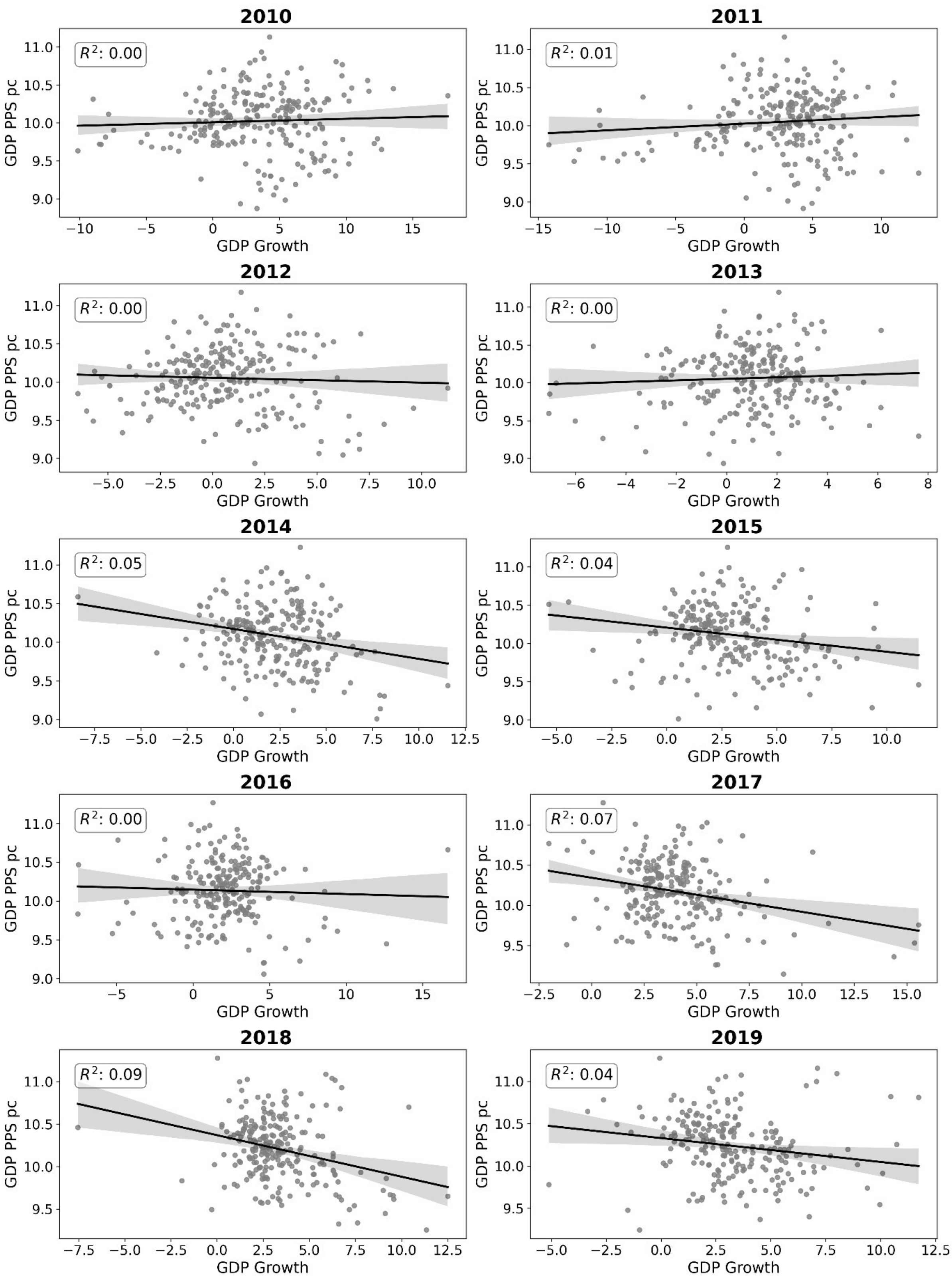

Figure A7 - GDP PPS pc growth and GDP PPS pc (logarithmic scale) correlation by year.

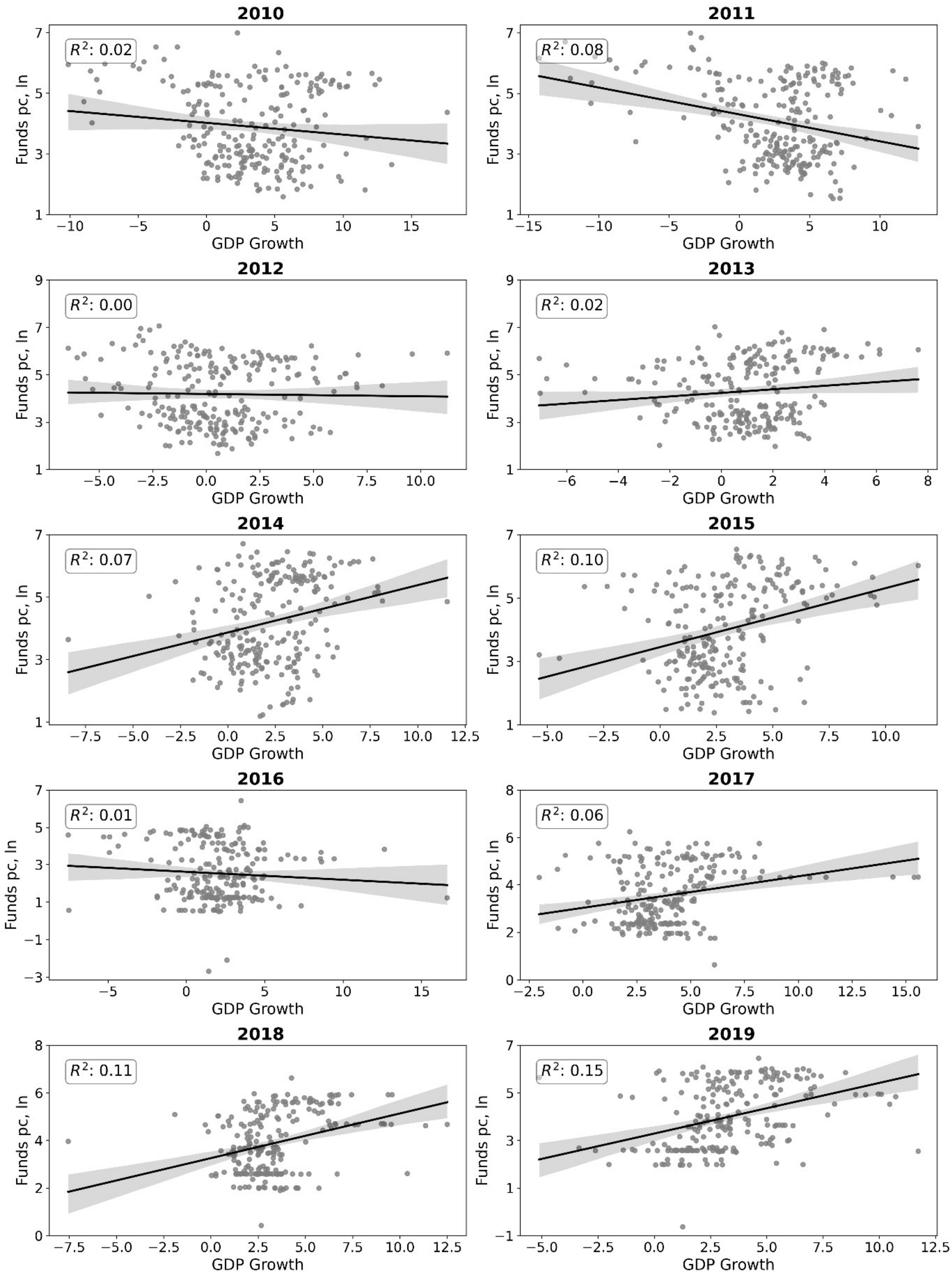

Figure A8 - GDP PPS pc growth and Funds (ERDF, ESF, and CF) expenditure per capita (logarithmic scale) correlation by year.

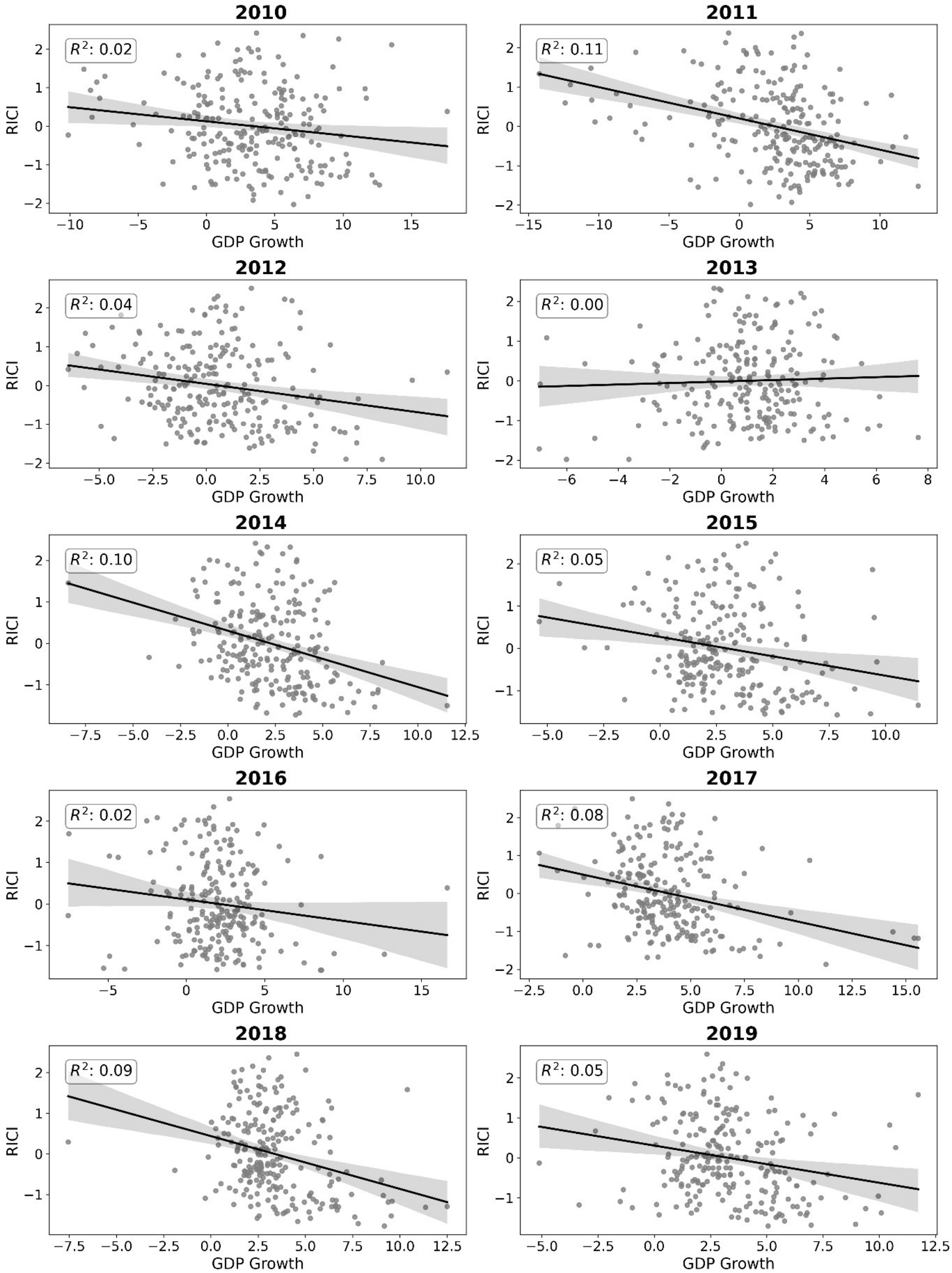

Figure A9 - GDP PPS pc growth and RICI correlation by year

9. APPENDIX B – ICI AND IAFC FOR NEW ENTRIES AND EXITS

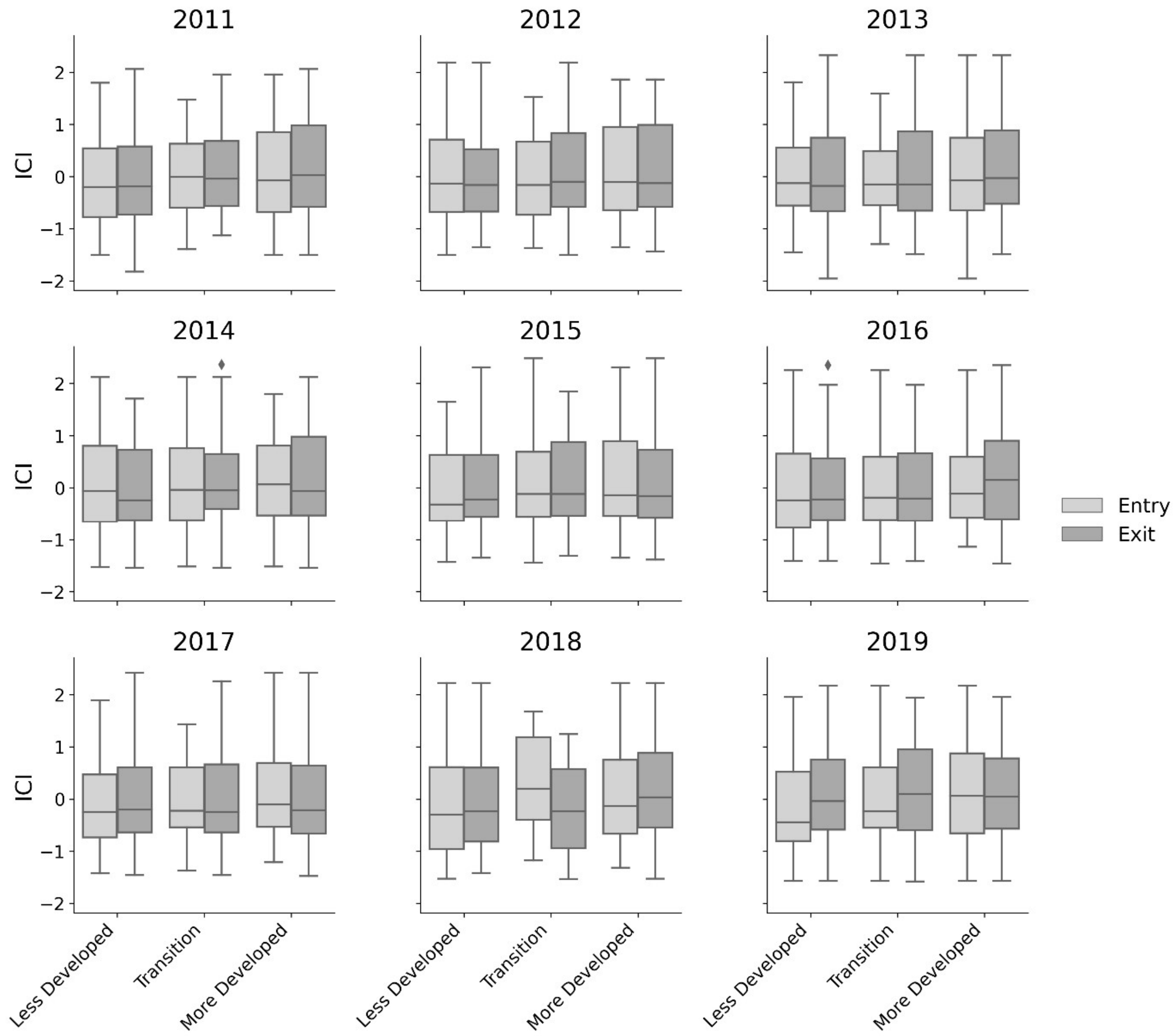

Figure B1 - Industrial Complexity Index (ICI) for new activities entries and exits for each group of regions from different eligible classifications - Less Developed, Transition, and More Developed - per year.

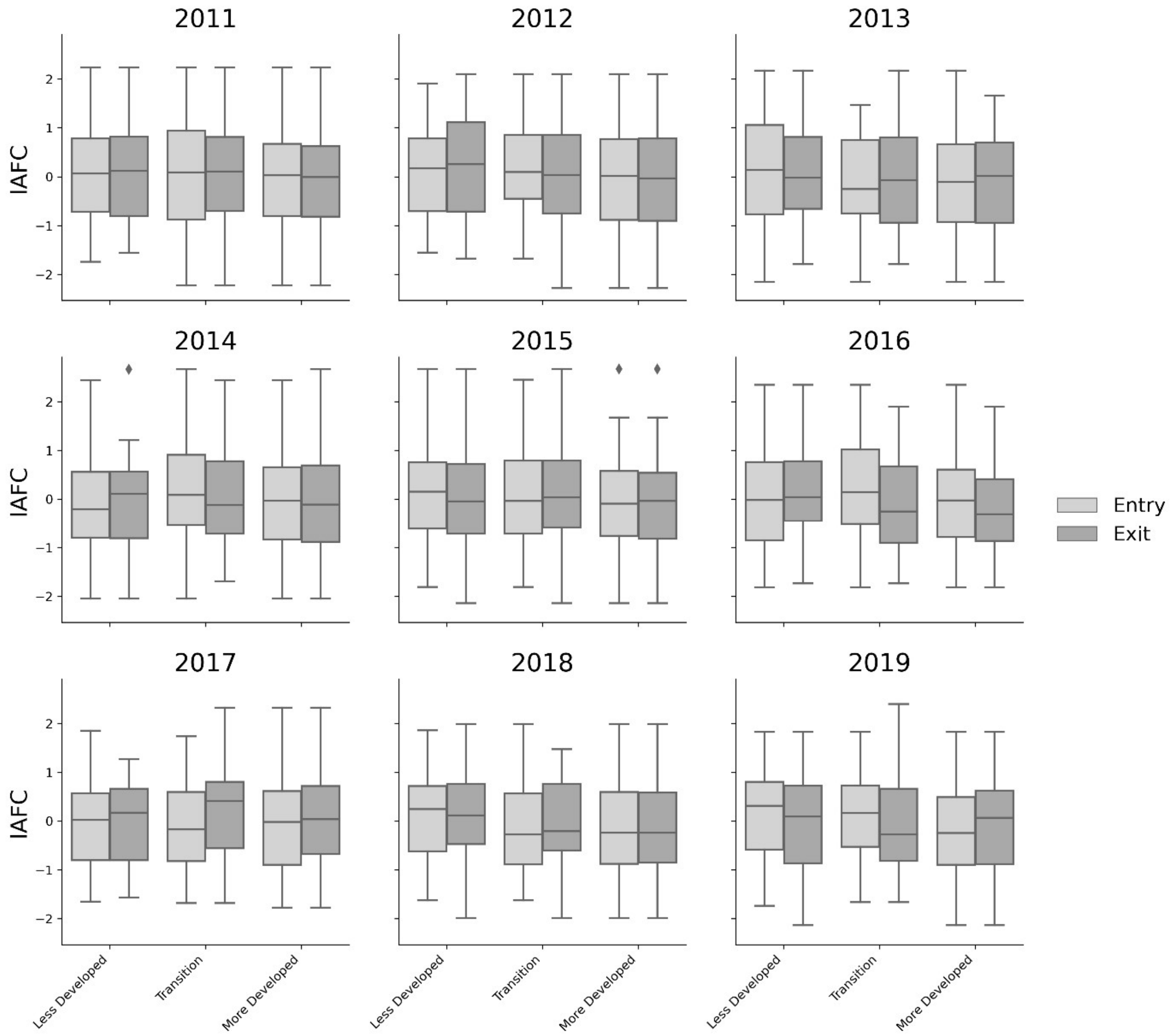

Figure B2 - Industrial Activity Funds Capture (IAFC) for new activities entries and exits for each group of regions from different eligible classifications - Less Developed, Transition, and More Developed - per year.

10. APPENDIX C – PRODUCT SPACE

To achieve sustainable growth, it is required to know the product structure to promote a structural transformation that will show the region's constraints and opportunities for diversity (Hartmann et al., 2019). As Hidalgo et al. (2007) showed, complexity methods are a solid framework for identifying regional constraints and uncovering development opportunities, guiding toward economic transformation.

Product Space, a network that links activities based on their proximity regarding capabilities, helps understand the path-dependent nature of economic diversification. It formalizes the idea that a region's ability to develop an activity depends on its ability to develop others. For example, economies proficient in furniture can more easily transition to producing wooden cabinets, while producing smartphones would be much more difficult. The skills, raw materials, machinery, and institutions required for furniture and cabinets are more aligned. Product Space provides a map showing where economies are more likely to develop new activities closely related to those they already have, deepening the understanding of economic diversification.

A method that assumes similar activities are close to each other is required to measure proximity. A matrix was built using the occupation dataset for each year from 2010 to 2019. Each row and column represents a particular activity, and each off-diagonal element represents the proximity between a pair of activities in a range of 68 different classes and 13 aggregations. The Maximum Spanning Tree (MST) algorithm was applied to this matrix. This algorithm included all 68 activity classes in a skeleton network, a tree containing a maximal sum of weights, which helped understand the relationships between different activities.

Figure C1 illustrates the Industrial Space as of 2019 for the 13 aggregations of the 68 activity classifications. Using a network representation for the product space, it is possible to see which activities are close to each other and the groups they form, their classifications, and their values. For that, colors and sizes were used. The nodes representing activities were painted according to the main activity class, realizing that activities in the same classes lie close and tend to form clusters. Links connect related activities. Nodes with few links or in the periphery also represent few related activities in these regions, and regions with more links or more centrality represent activities with many related activities.

Moreover, betweenness centrality was used for size. It measures the degree nodes with the shortest paths between other nodes. A node with high betweenness centrality is important for the flow of information within the network, as it acts as an intermediary between other nodes. Nodes with high betweenness centrality have a higher influence on the spread of information and are strategic in the network.

Some classes have high betweenness centrality, which is essential for opening the path to the other. The 2019 results show that activities related to electricity, manufacturing, construction, or even transporting and storage are meaningful, enabling regions to shift towards more complex activities.

Figure C1 - Industrial Space 2019.

Appendix D provides the NACE Table, which can be consulted to identify the aggregation group to which each activity belongs.

11. APPENDIX D – NACE TABLE

Nace Code	Nace Description
A	**Agriculture, forestry and fishing**
A01	Crop and animal production, hunting and related services
A02	Forestry and logging
A03	Fishing and aquaculture
B	**Mining and quarrying**
B05	Mining of coal and lignite
B06	Extraction of crude petroleum and natural gas
B07	Mining of metal ores
B08	Other mining and quarrying
B09	Mining support service activities
C	**Manufacturing**
C10	Manufacture of food products
C11	Manufacture of beverages
C12	Manufacture of tobacco products
C13	Manufacture of textiles
C14	Manufacture of wearing apparel
C15	Manufacture of leather and related products
C16	Manufacture of wood and of products of wood and cork, except furniture
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31	Manufacture of furniture
C32	Other manufacturing
C33	Repair and installation of machinery and equipment
D	**Electricity, gas, steam and air conditioning supply**
D35	Electricity, gas, steam and air conditioning supply
E	**Water supply; sewerage; waste managment and remediation activities**
E36	Water collection, treatment and supply
E37	Sewerage
E38	Waste collection, treatment and disposal activities; materials recovery
E39	Remediation activities and other waste management services
F	**Construction**
F41	Construction of buildings
F42	Civil engineering
F43	Specialised construction activities
G	**Wholesale and retail trade; repair of motor vehicles and motorcycles**
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H	**Transporting and storage**
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities

Nace Code	Nace Description
I	**Accommodation and food service activities**
I55	Accommodation
I56	Food and beverage service activities
J	**Information and communication**
J58	Publishing activities
J59	Motion picture, video and television programme production
J60	Programming and broadcasting activities
J61	Telecommunications
J62	Computer programming, consultancy and related activities
J63	Information service activities
K	**Financial and insurance activities**
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L	**Real estate activities**
L68	Real estate activities
M	**Professional, scientific and technical activities**
M69	Legal and accounting activities
M70	Activities of head offices; management consultancy activities
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74	Other professional, scientific and technical activities
M75	Veterinary activities
N	**Administrative and support service activities**
N77	Rental and leasing activities
N78	Employment activities
N79	Travel agency, tour operator and other reservation service and related activites
N80	Security and investigation activities
N81	Services to buildings and landscape activities
N82	Office administrative, office support and other business support activities
O	**Public administration and defence; compulsory social services**
O84	Public administration and defence; compulsory social services
P	**Education**
P85	Education
Q	**Human health and social work activities**
Q86	Human health activities
Q87	Residential care activities
Q88	Social work activities without accommodation
R	**Arts, entertainment and recreation**
R90	Creative, arts and entertainment activities
R91	Libraries, archives, museums and other cultural activities
R92	Gambling and betting activities
R93	Sports activities and amusement and recreation activities
S	**Other services activities**
S94	Activities of membership organisations
S95	Repair of computers and personal and household goods
S96	Other personal service activities
T	**Activities of households as employers; undifferentiated goods - and services - producing**
T97	Activities of households as employers of domestic personnel
T98	Undifferentiated goods- and services-producing activities of private households for own use
U	**Activities of extraterritorial organisations and bodies**
U99	Activities of extraterritorial organisations and bodies

12. APPENDIX E – CONVERGENCE ANALYSIS

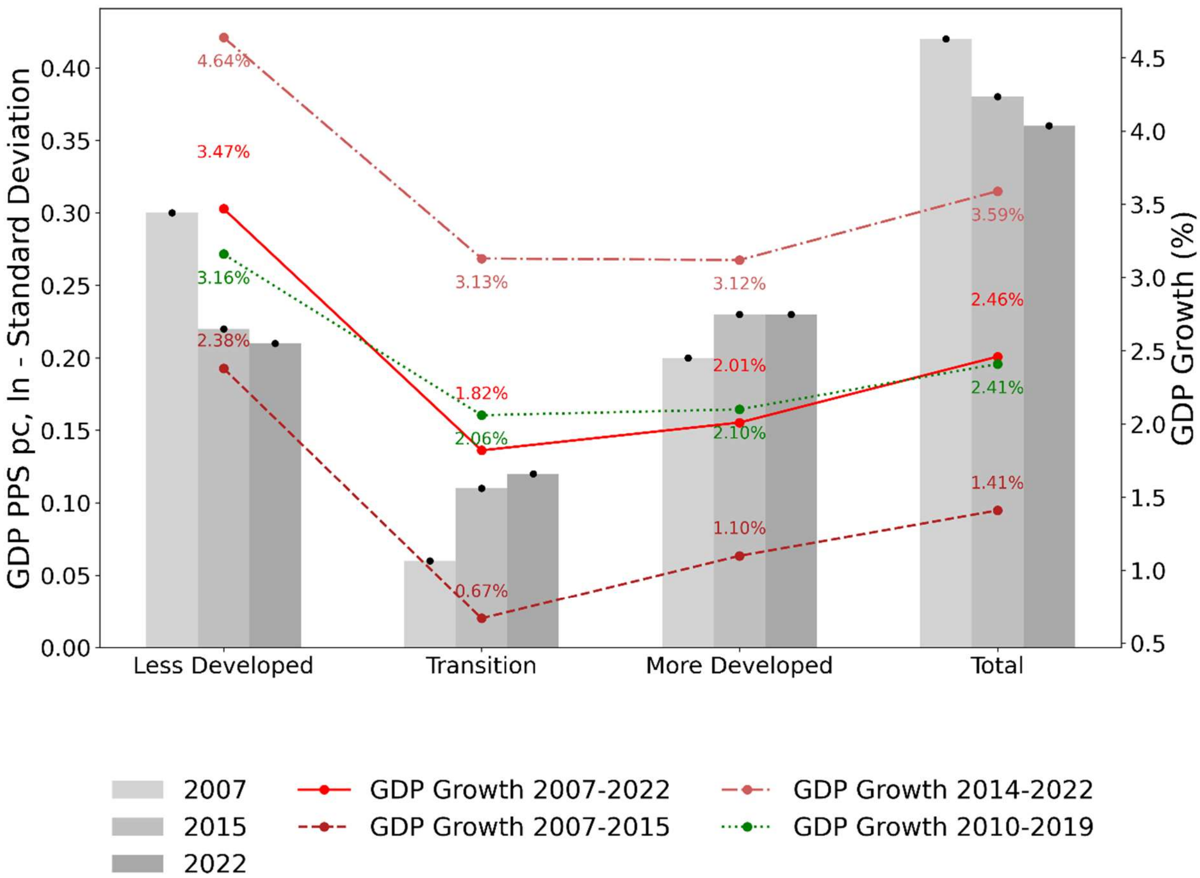

Figure E1 - For each eligible classification region - less developed, transition, more developed – and the total of 231 NUTS 2 regions, the standard deviation of GDP PPS pc (logarithm scale) for 2007, 2015, and 2022 and the annual GDP Growth between 2007 and 2022 (beginning and end of expenditure from the 2007-13 and 2014-20 programs), the annual GDP Growth between 2007 and 2015 (beginning and end of expenditure from the 2007-13 program)), the annual GDP Growth between 2014 and 2022 (beginning and end of expenditure from the 2014-20 program) and the annual GDP Growth between 2010 and 2019 (complexity analysis period).

13. APPENDIX F – PATENTS

Patents reflect region’s innovative capacity through new technologies. A parallel analysis was conducted in this thesis to seek more insights. The patents dataset is from the Organization for Economic Cooperation and Development's (OECD) REGPAT as of January 2024. It includes 35 technological classes, which aggregate two-digit Cooperative Patent Classification (CPC) groups across 235 EU NUTS-2 regions. To mitigate the noise and outliers in the dataset, a three-year moving average was applied to smooth the dataset, and regions with low patents, less than 50 on average by year, were excluded. This method was chosen to reduce the impact of short-term fluctuations. For the patent data, the analysis covers the same period as the fund programs, starting in 2007 (the first program's launch) and extending to 2022, the final year of expenditures of the last program in analysis, which allows for a comprehensive 16-year analysis.

The regional complexity indicator, ECI, will be referred to as the Regional Technological Complexity Index (RTCI), and the Technological Complexity Index (TCI) for PCI. Through the iteration presented in equations (5) and (6), the PCI and ECI for Technologies in European regions were estimated annually from 2007 to 2022.

Using the same reference year for the industries, 2019, Table F1 highlights the top and bottom ten regions in terms of complexity. Regions with high RTCI scores, such as Stockholm, Östra Mellansverige and Övre Norrland in Sweden, as well as Oberbayern in Germany, and Bretagne and Provence Alpes Côte d'Azur in France, are among the top ten regions for complexity level. On the other side, RTCI scores include Emilia-Romagna and Veneto in Italy, and some regions from Germany, like Weser-Ems, Lüneburg, and Kassel, are some examples of regions with low technological complexity.

Table F2 displays the top and bottom ten complexity activities. Like Industrial complexity, communication and IT scientific technology activities rank highest from the Technological perspective, indicating areas where only a few regions can attain comparative advantages. In contrast, many European regions demonstrate comparative advantages, mainly in machinery, manufacturing, and mechanical technologies.

Table F1 – Top and Bottom ten regions by complexity for technologies (RTCI), 2019.

#	NUTS-2	Region	RTCI
1	SE11	Stockholm	3.65
2	FR52	Bretagne	3.07
3	DE21	Oberbayern	2.24
4	FR82	Provence Alpes Côte d'Azur	2.03
5	SE12	Östra Mellansverige	1.95
6	FI19	Lansi-Suomi	1.87
7	HU10	Közép-Magyarország	1.85
8	SE33	Övre Norrland	1.80
9	ES30	Comunidad de Madrid	1.77
10	FI1B	Helsinki-Uusimaa	1.61
…	…	…	…
146	FR23	Haute-Normandie	-1.31
147	DE73	Kassel	-1.32
148	SE32	Mellersta Norrland	-1.34
149	DEA1	Düsseldorf	-1.37
150	NL13	Drenthe	-1.39
151	DE93	Lüneburg	-1.44
152	AT31	Oberösterreich	-1.59
153	DE94	Weser-Ems	-1.61
154	ITH3	Veneto	-1.62
155	ITH5	Emilia-Romagna	-1.75

Table F2 – Top and Bottom ten activities by complexity for technologies (TCI), 2019.

#	Technology	TCI
1	Digital communication	2.37
2	Computer technology	2.19
3	Telecommunications	1.93
4	Audio-Visual technology	1.29
5	Basic communication processes	1.15
6	IT methods for management	1.04
7	Measurement	0.83
8	Optics	0.81
9	Micro_Structural and nano-technology	0.59
10	Control	0.59
…	…	…
26	Macromolecular Chemistry, polymers	-0.84
27	Surface technology, coating	-0.84
28	Other consumer goods	-0.86
29	Textil and paper machines	-0.94
30	Thermal processes and apparatus	-0.97
31	Furniture, games	-1.01
32	Other special machines	-1.04
33	Handling	-1.15
34	Mechanical elements	-1.20
35	Machine tools	-1.45

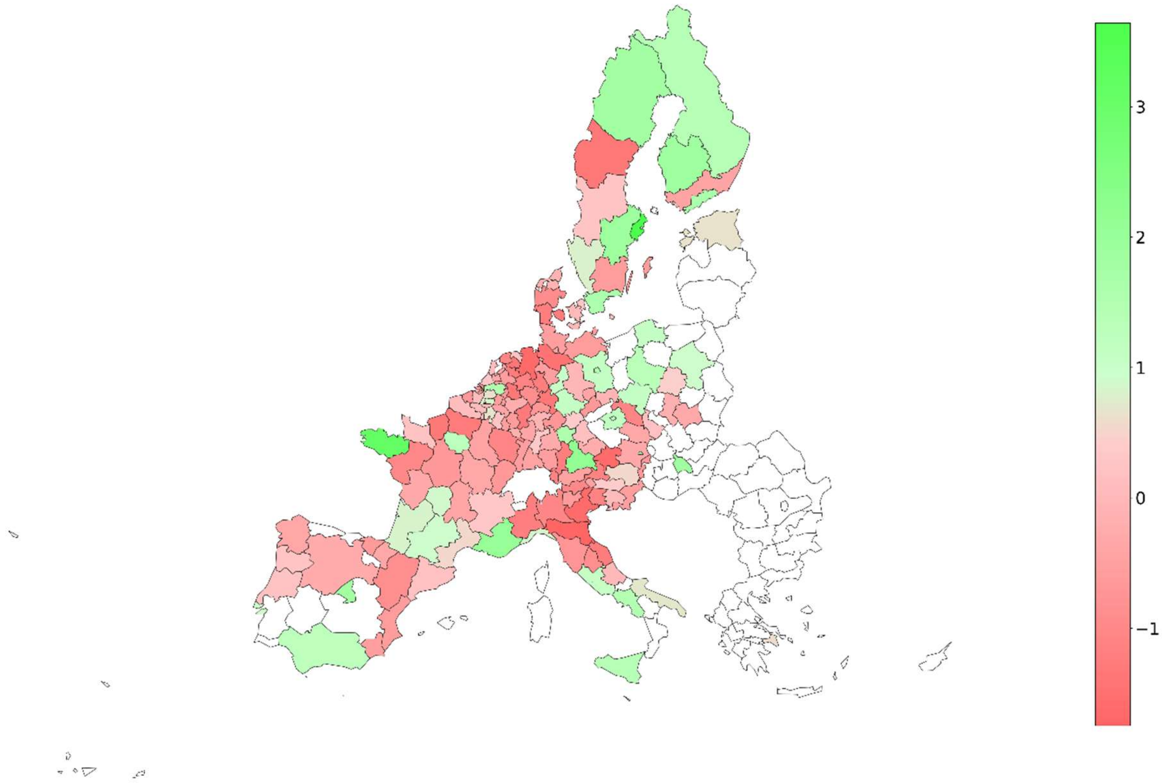

Figure F1 – RTCI for each of the 155 regions in Europe, from the regions with low complexity (Red) to the ones with high complexity (Green), 2019.

The map from Figure F1 illustrates the RTCI scores from European regions for 2019, arranged from regions with low complexity (indicated in red) to those with high complexity (shown in green). The color gradient highlights the varying levels of complexity in activities among these regions, providing a clear visual representation of their relative positions. It is possible to understand that several regions without patents or very few were excluded.

From the point of view of the regions and activities capable of attracting funds, Tables F3 and F4 display the new indicators AFC and RFC, which were called Technological Regional Funds Capture (TRFC) and Technological Activities Funds Capture (TAFC).

Table F3 highlights which activities have a greater or lesser capacity to attract funds from a technological perspective (TAFC). Activities such as Pharmaceutics, IT, Electrical machinery, and Optics demonstrate a strong ability to capture funds. In contrast, activities with less capacity to attract funds include chemistry, machinery, or communication.

Comparing these results with the 2019 TCI from the point of view of Technologies, conversely, to the Industries, there is a smooth positive correlation between an activity's complexity and its ability to capture funds, which indicates that more complex activities tend to receive more funds, as shown in Figure F2. These patterns remain consistent yearly between TCI and TAFC, Figure F10.

Table F3 – Top and Bottom ten activities with the capacity to capture funds, in 2019 by technologies (TAFC)

#	Technology	TAFC
1	Pharmaceuticals	2.35
2	IT methods for management	2.19
3	Analysis of biological materials	1.93
4	Control	1.29
5	Computer technology	1.13
6	Electrical machinery, apparatus, energy	1.05
7	Organic fine chemistry	0.82
8	Furniture, games	0.82
9	Medical technology	0.60
10	Thermal processes and apparatus	0.55
…	…	…
26	Other consumer goods	-0.84
27	Handling	-0.93
28	Basic communication processes	-0.94
29	Surface technology, coating	-1.02
30	Machine tools	-1.23
31	Semiconductors	-1.27
32	Audio-visual technology	-1.29
33	Other special machines	-1.33
34	Basic materials chemistry	-1.36
35	Macromolecular chemistry, polymers	-1.48

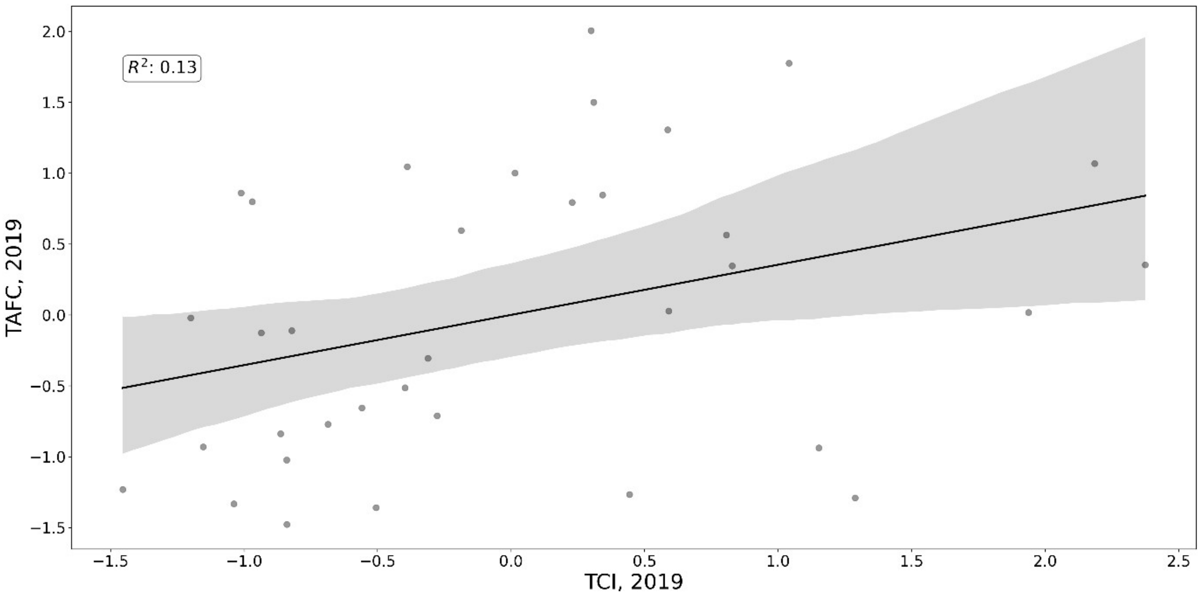

Figure F2 – Correlation between TCI and TAFC, 2019

Regarding regions, from the technological perspective, regions from Praha, Střední Morava, and Střední Čechy in the Czech Republic; Lazio, Liguria, and Campania in Italy; and Estonia (Eesti) demonstrate high capability to attract funds. But Düsseldorf and Lüneburg in Germany, Limburg and Zeeland in the Netherlands, Auvergne, Picardie, and Haute-Normandie in France represent regions that struggle to attract funds based on the technological activities assessed in each region.

Table F4 – Top and Bottom ten regions with the capacity to capture funds in 2019 by technologies (TRFC)

#	NUTS-2	Region	TRFC
1	CZ01	Praha	3.03
2	CZ07	Střední Morava	2.86
3	EE00	Eesti	2.68
4	PL63	Pomorskie	2.02
5	ITI4	Lazio	1.97
6	CZ02	Střední Čechy	1.91
7	ITC3	Liguria	1.82
8	AT13	Wien	1.75
9	ITF3	Campania	1.75
10	HU10	Közép-Magyarország	1.60
…	…	…	…
146	DEA1	Düsseldorf	-1.53
147	AT22	Steiermark	-1.55
148	NL42	Limburg	-1.60
149	ITH5	Emilia-Romagna	-1.74
150	DE93	Lüneburg	-1.81
151	FR23	Haute-Normandie	-1.91
152	FR72	Auvergne	-1.92
153	FR22	Picardie	-1.93
154	AT21	Kärnten	-2.02
155	NL34	Zeeland	-2.02

Comparing the results of TRFC with those of RTCI, 2019 as a reference year, it is possible to observe a positive correlation between a region's complexity and its ability to attract funding in the technological sector, as shown in Figure F3. This suggests that more complex regions tend to receive more funds. These patterns remain consistent yearly between RTCI and TRFC, Figure F8.

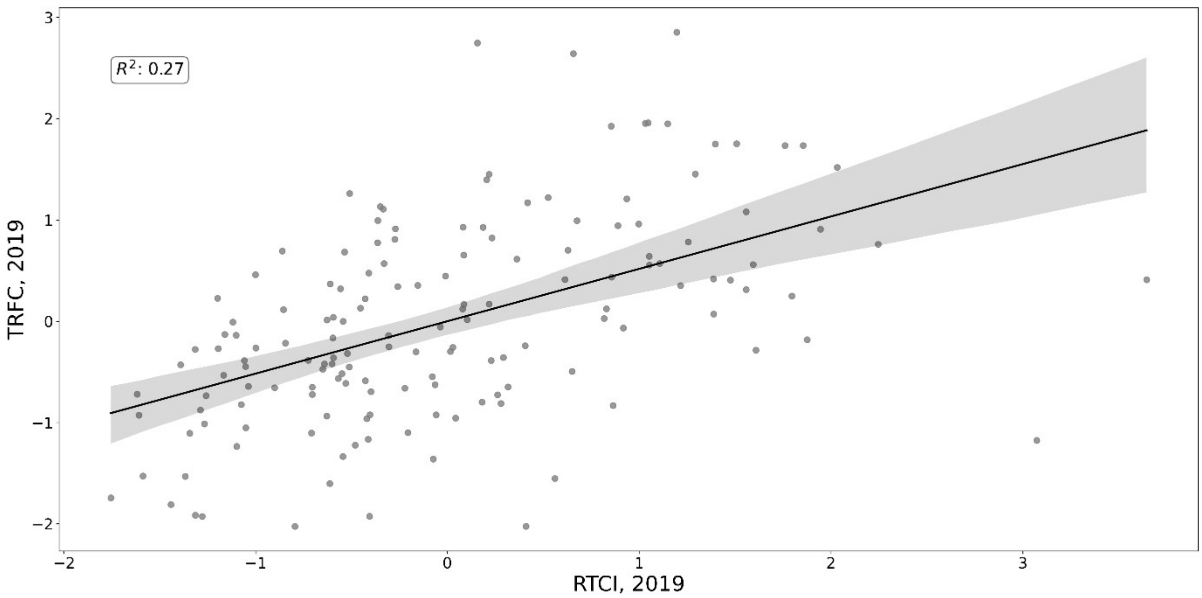

Figure F3 – Correlation between the average of RTCI Ranking and TRFC, 2019.

Finally, it is possible to confirm that the TRFC correlates with the funds. Figure F4 compares the 2019 TRFC and the 2019 funds expenditures, showing that the higher the TRFC (high capability to capture funds), the higher the total funds these regions received. These patterns remain consistent yearly, as shown in Figure F9.

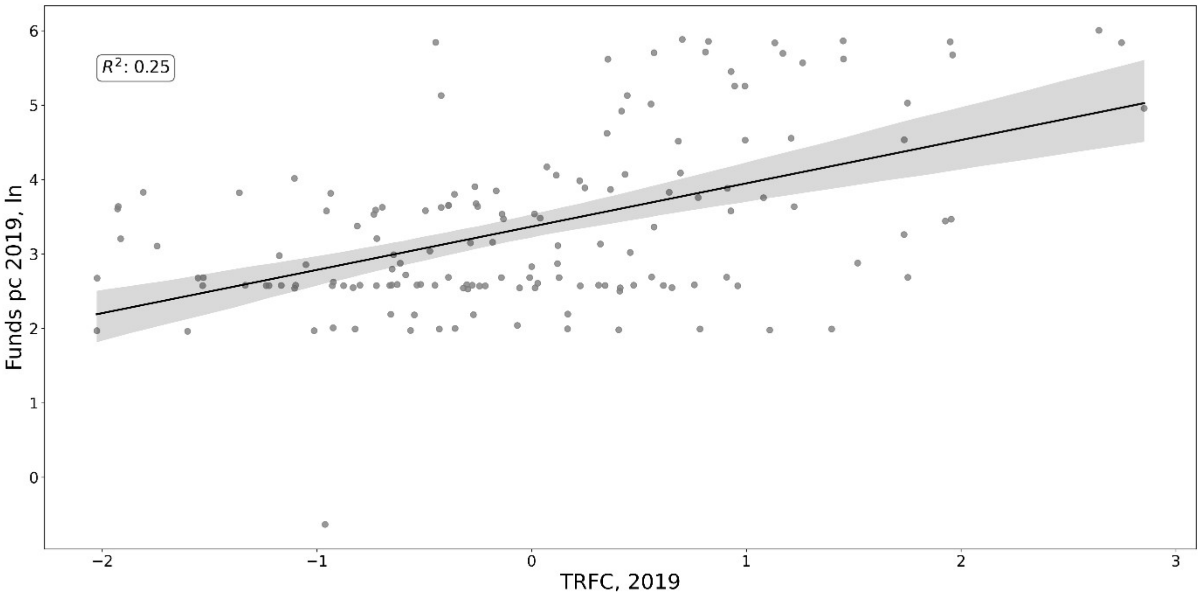

Figure F4 – Correlation between TRFC and funds, 2019.

For the analyzed period, the portfolio of complex activities in the EU was examined by measuring the Pearson correlation between relatedness density and the technological complexity index (TCI). The correlation, as a function of RTCI, reveals an S-shaped curve, showing a non-linear relationship that aligns with the notion that regions pass through distinct stages of economic development (Pinheiro, Balland, et al., 2022). A positive correlation coefficient indicates that a region has proximity to complex activities, while a negative correlation coefficient implies proximity to simpler activities. Regions with a high density of comparative advantages in related activities are more likely to shift towards more complex products, thereby increasing regional complexity (Balland, 2019), as shown in Figure F5A.

Additionally, the same correlation exercise, with relatedness density, was applied to the newly developed Regional Funds Capture (TRFC) indicator. This dataset revealed distinct results from Industries, aligning with prior findings. As illustrated in Figure F5B, TRFC does not show an S shape despite the same direction but is much more spread, suggesting that complexity and funds allocation might follow the same trajectories. Higher complexity levels of activities and regions are slightly related to the capability to capture funds (Figure F5B).

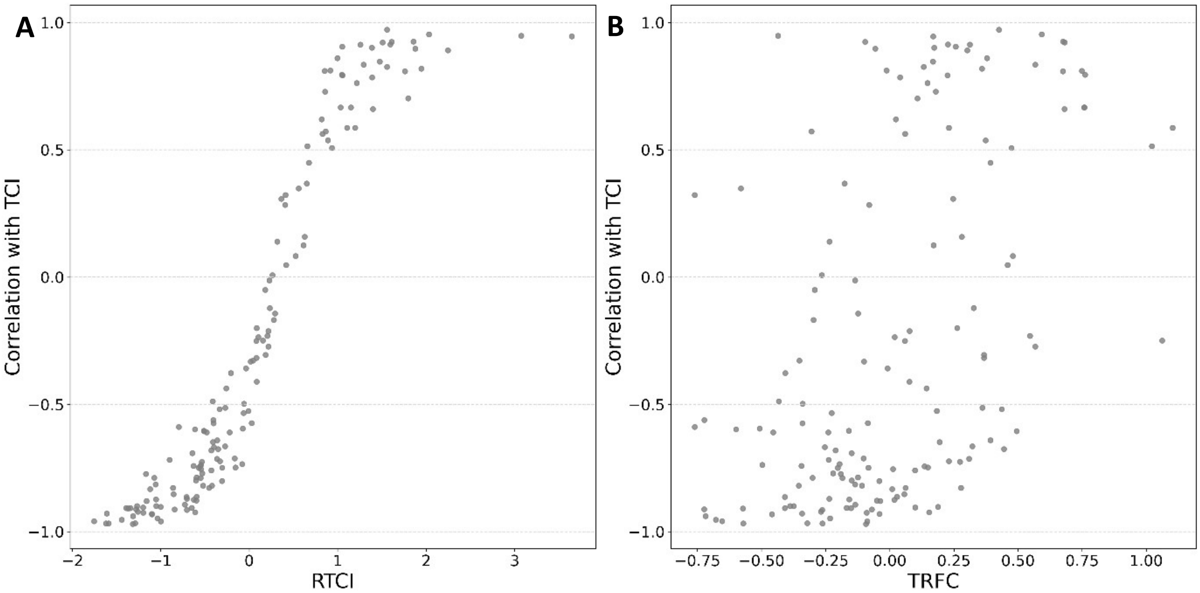

Figure F5 – **A**. Correlation between relatedness density and Technological Complexity Index (TCI) as a function of the Regional Technological Complexity Index (RTCI), 2019. **B**. Correlation between relatedness density and Technological Complexity Index (TCI) as a function of the Technological Regional Funds Capture (TRFC), 2019.

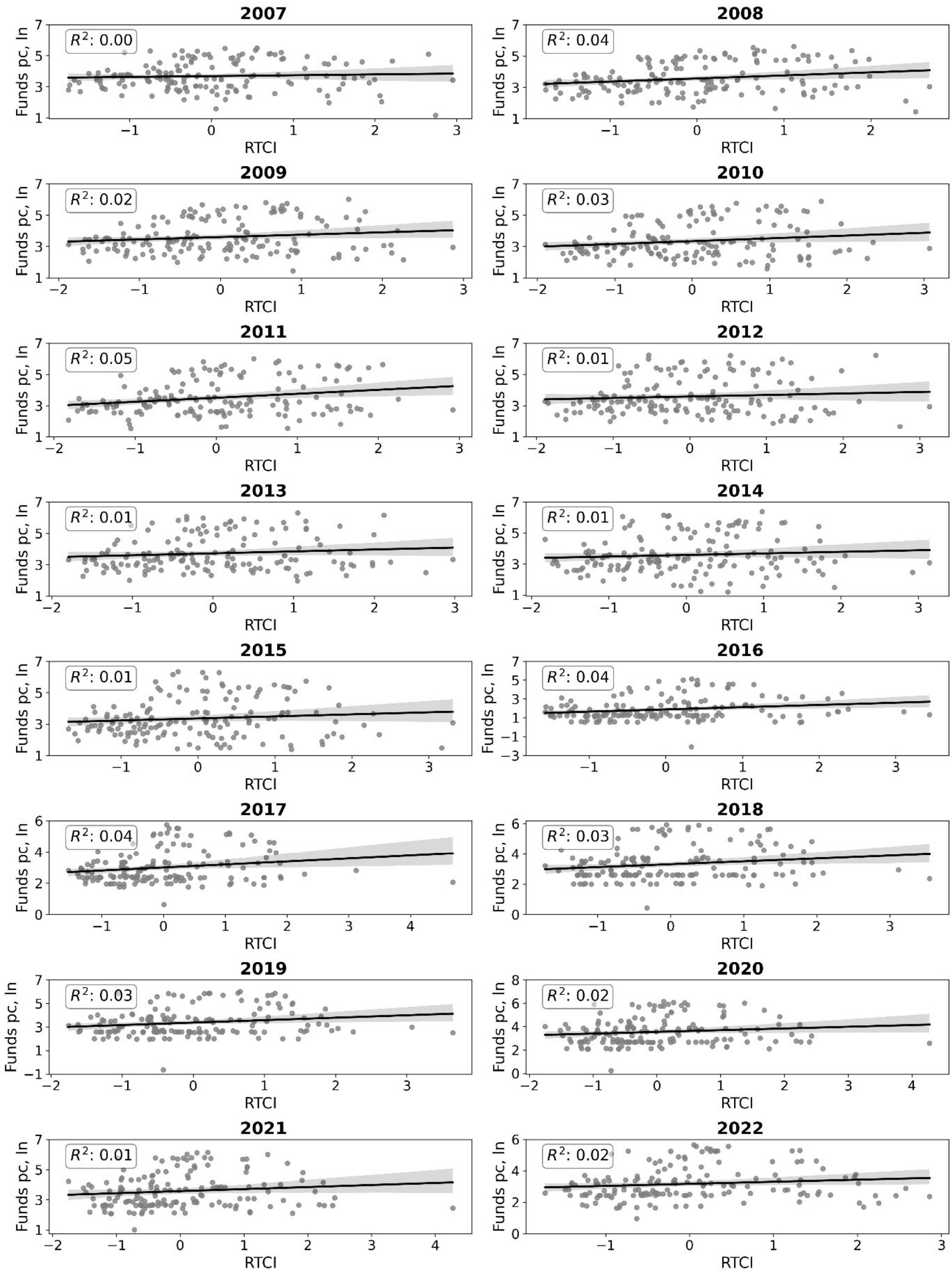

Figure F6 - RTCI and and Funds (ERDF, ESF, and CF) expenditure per capita (logarithmic scale) correlation by year

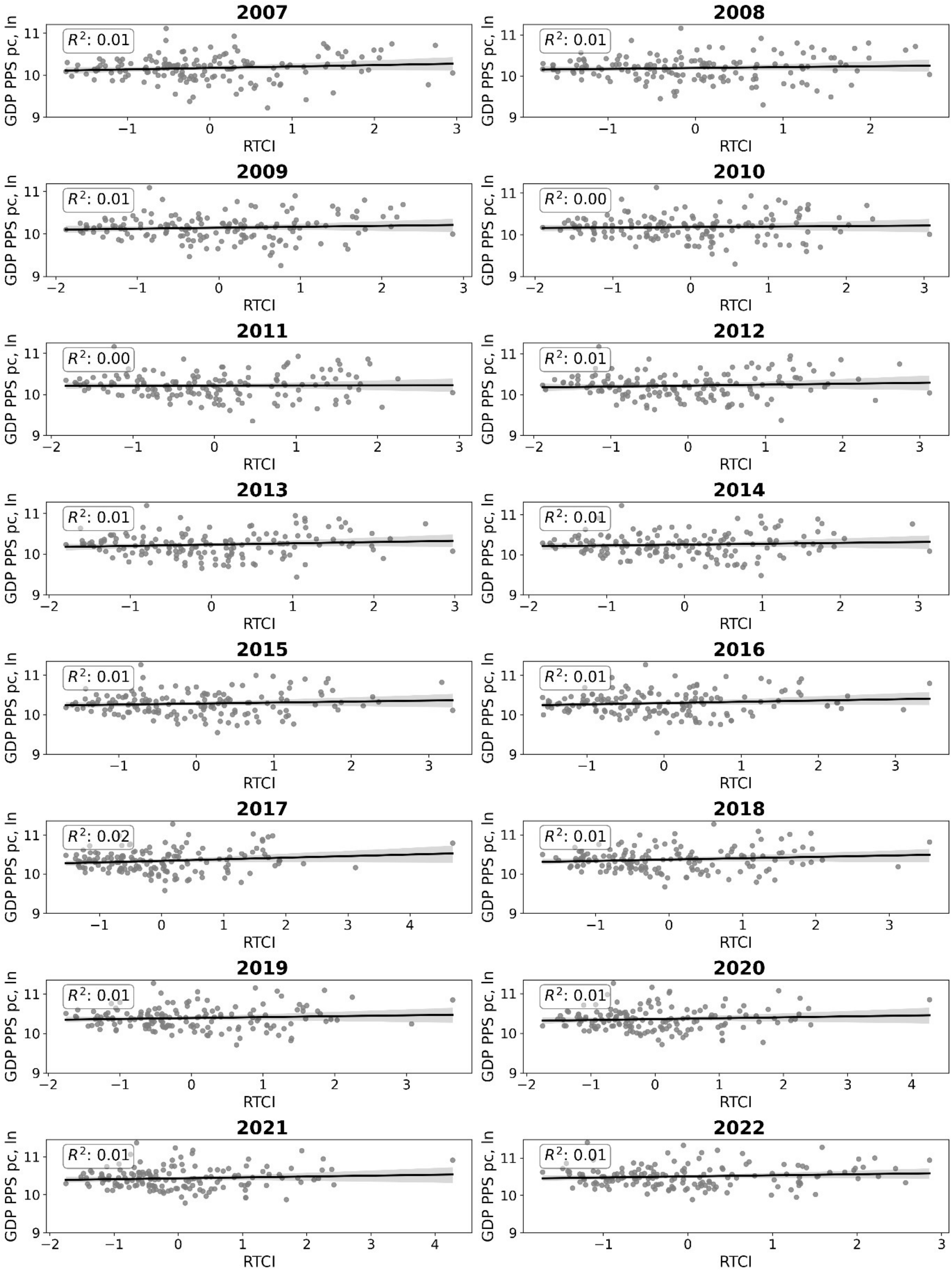

Figure F7 - TCI and GDP PPS per capita (logarithmic scale) correlation by year.

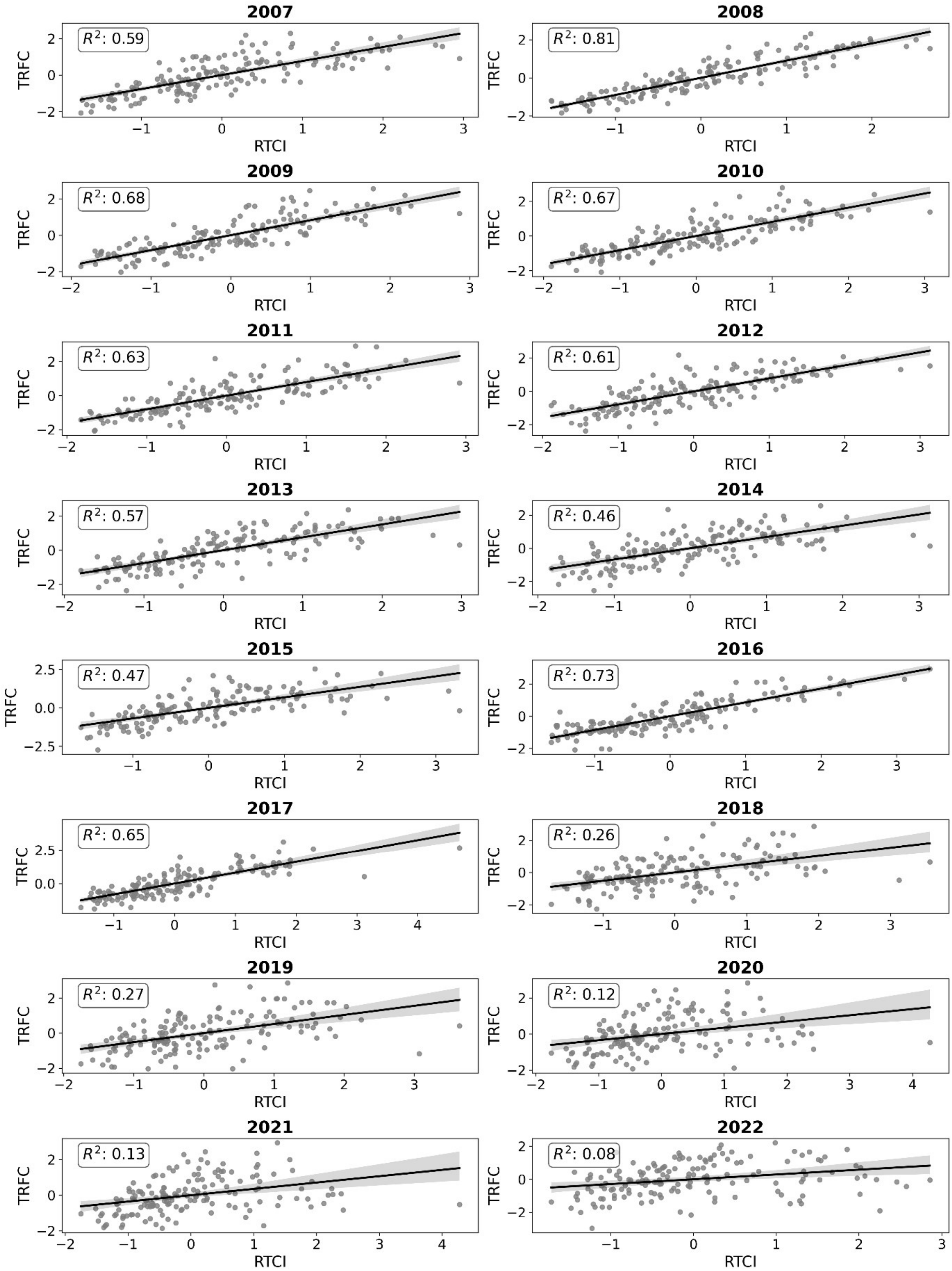

Figure F8 - RTCI and TRFC correlation by year

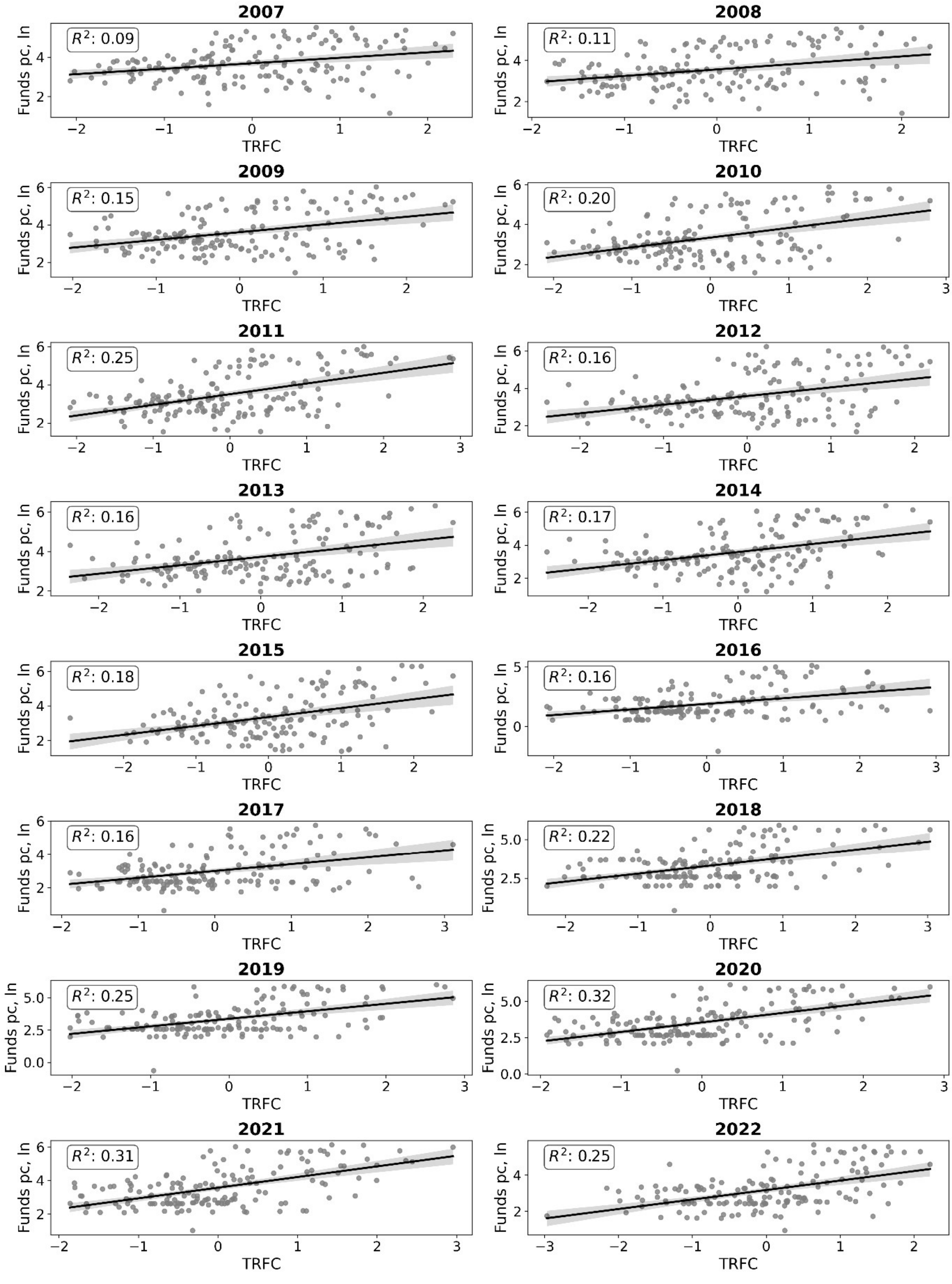

Figure F9 - TRFC and Funds (ERDF, ESF, and CF) expenditure per capita (logarithmic scale) correlation by year

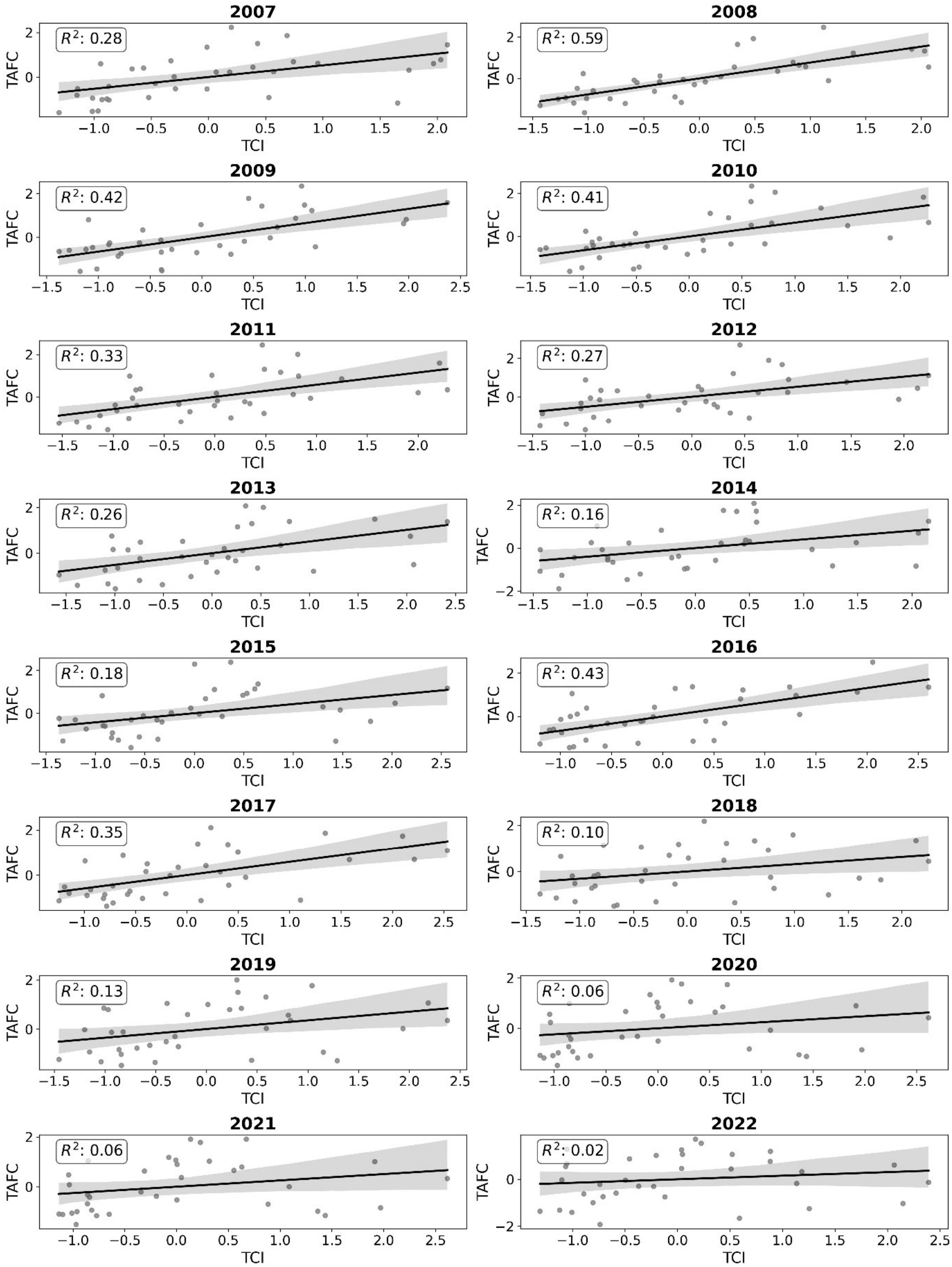

Figure F10 - ICI and IAFC correlation by year

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