LUND UNIVERSITY
School of Economics and Management

European Cohesion Policy and Regional Performance

A Regression Discontinuity Approach with Analysis of Spillover Effects: 2007-2020

Samuel M Arfwedson

Master's Program in Economics
Department of Economics
Master's Thesis II (15 credits ECTS)
Date of seminar: 2024-05-30
Supervisor: Maria Persson

Abstract: This thesis examines the impact of the European Cohesion Policy on regional economic performance during the funding periods of 2007-2013 and 2014-2020, using a Regression Discontinuity Design (RDD) and spatial econometric techniques. The analysis leverages the eligibility rule, which grants additional funding to regions with a GDP per capita below 75% of the EU average, creating a natural experiment to assess the policy's effectiveness. The findings reveal that the Cohesion Policy's impact varied between the two periods. Specifically, the 2014-2020 period demonstrated a positive effect on regions barely meeting the funding threshold, while the 2007-2013 period showed no significant effects. Moreover, although the spatial analysis revealed significant interdependence among regions, there was no conclusive evidence of indirect effects of the policy. However, the positive impacts observed during the 2014-2020 period remained robust even when accounting for spatial spillovers. The relative success in 2014-2020 may suggest that the shift towards a more place-based policy approach was more effective than the narrower focus on convergence in the earlier period, or it may highlight the policy's limitations during economic crises. [†]

Keywords: European Union, Regression Discontinuity, Regional Policy, Spatial Econometrics, Cohesion Policy

[†] I would like to express my utmost gratitude to my supervisor, Maria Persson, for her invaluable insights and support throughout the thesis. I am also grateful for the constructive comments and feedback received during the Master Thesis Conference, jointly organized by Lund University and the University of Porto. Furthermore, I would like to extend my appreciation to my friends and family for their unwavering support and encouragement.

Contents

List of Figures

List of Tables

1

Introduction

Economic disparities across countries and regions within the European Union (EU) remain a significant challenge, undermining the European goal of economic cohesion and integration. Many regions have been trapped in a cycle of economic decline, experiencing lower growth, employment and productivity which has fueled political discontent and unrest, often manifested as support for Euroskeptic parties (Dijkstra et al., 2020). To address these disparities, the EU has implemented a system of public transfers known as the Cohesion Policy, aimed at fostering structural and economic homogeneity among member states and regions. The importance of the Cohesion Policy has grown over time: from less than 10% of the budget in the 1970s to almost one third (32.2%) of the 2014-20 budget (Fratesi, 2024).

With the accession of the Southern European countries - Greece, Spain and Portugal - in the 1980s, the considerable developmental differences among member states and their regions became more pronounced. As concerns about the sharp competitive pressures these countries might face upon entering the Single Market grew, especially in the light of the strict policies on the public debt, the increase in funds allocated to regional policy enabled these nations to maintain a controlled deficit while continuing to invest in strategic areas (Dicharry et al., 2019). With the German Reunification in 1990 and the Eastern enlargements in 2004, 2007 and 2013, the importance of these considerations were strengthened and today the Cohesion budget is the second largest category after the Common Agricultural Policy (CAP). For the funding period of 2021-2027, €392 billion has been allocated, with the vast majority is directed towards less developed regions (European Commission, 2024).

The body of research evaluating the impact of the EU Cohesion Policy on various metrics, particularly economic growth, is extensive. However, the literature reveals a lack of consensus on the outcomes of this policy. While some studies indicate a positive impact on economic growth, others report insignificant or even negative effects (Dall'Erba and Fang, 2017). One challenge in many studies evaluating the policy is the issue of endogeneity - meaning that unobserved factors simultaneously affect both the policy outcomes and the allocation of funding. As a result, it becomes difficult to ascertain whether observed economic growth in funded regions is genuinely attributable to the policy itself or if it merely reflects these underlying, unobserved factors. This problem is particularly acute when comparing regions at different stages of development. Standard economic theory, such as the convergence hypothesis, suggests that less developed regions are expected to grow faster than more developed ones, naturally catching up over time (Barro and Sala-i Martin, 1992). This natural growth dynamic can confound the effects of regional policies, making it challenging to isolate the impact of the policy from the general trend of economic convergence.

To address these concerns and isolate the causal effect of the Cohesion Policy on economic outcomes on economic growth, previous research has employed a quasi-experimental Regression-Discontinuity Design (RDD). This approach has been demonstrated in studies evaluating earlier programming periods, notably by Becker et al. (2010, 2018) and Pellegrini et al. (2013). The method leverages the policy's funding rule, which provides additional resources to regions below a specific GDP per capita threshold - 75% of the EU average. The strength of RDD lies in its ability to simulate a randomized experiment by comparing regions that are similar in all respects except for their position relative to this predefined GDP threshold. Regions just above the threshold do not receive extra funding, while those just below do. This setup allows researchers to attribute differences in economic outcomes directly to the impact of the Cohesion Policy, thereby providing a reliable estimation of its effects on regional economic growth (Angrist and Pischke, 2009).

In this study, the aim is contribute to the research on the EU's cohesion policy in two significant ways. Firstly, by building on prior research that employed a RDD approach by conducting an *ex-post* evaluation covering the most recent completed programming periods of 2007-2013 and 2014-2020. This extension not only allows for an examination of the policy's effects within a more recent timeframe but also provide a more comprehensive assessment of its impact following the 2004, 2007 and 2013 enlargements, which predominantly included Eastern European countries. These countries were almost uniformly classified under the "less developed" status, thereby offering a richer context to evaluating the policy's effectiveness in a setting where the Cohesion Policy's framework has evolved significantly.

Secondly, this study extends beyond the typical focus on direct regional impacts to explore the indirect, cross-regional spillover effects of the Cohesion Policy on economic growth. Cross-regional spillover effects refer to the impact that the policy interventions in one region can have on neighbouring regions, which may manifest through various channels such as enhanced infrastructure that improves connectivity and reduces transportation costs across regional boundaries. Although the literature, including works by Fidrmuc et al. (2024) and others, acknowledges the importance of these spillovers from the EU Cohesion Policy, there remains a gap in quantifying these effects using RDD which allows for a more reliable and precise estimation of the causal impacts.

This fills both a theoretical and methodological purpose. The regional growth trajectory in a highly integrated market like the EU, regions are expected to exhibit significant spillovers among each other due to factors such as trade flows, labor mobility, and shared resources, aligning with principles from the New Economic Geography (NEG) literature (Krugman, 1991). It is both expected and explicitly desired by the EU that the policy should impact neighboring regions (EUR-lex, 2021). Methodologically, the presence of indirect treatment effects between regions violate the *non-interference* assumption that is crucial in RDD (Imbens and Rubin, 2015). However, addressing potential cross-sectional dependencies that could clarify these indirect effects is notably overlooked in RDD research (Cornwall and Sauley, 2021). This approach is crucial for accurately capturing the full impact of the Cohesion Policy, and offers insights into the broader efficacy of regional development strategies within the EU.

This thesis seeks to answer several key questions regarding the effectiveness of the European Cohesion Policy: Has the program achieved its intended outcomes, particularly in promoting economic growth in eligible regions? To what extent has the Cohesion Policy in one region influenced economic growth in neighboring regions? Are there significant spillover effects, and do these enhance or undermine the policy's effectiveness? This approach addresses the effectiveness of regional policy across spatial boundaries and provides deeper insights into the broader economic impacts of these policies.

The results indicate a differential impact of the policy across regions and programming periods. The 2014-2020 period demonstrated a positive effect on GDP per capita growth, while no significant impacts were observed during the 2007-2013 period. Additionally, while significant spatial interactions were found in the data, there was no conclusive evidence of indirect treatment effects from policy interventions in neighboring regions. Nevertheless, the positive impacts observed during the 2014-2020 period remained robust even when accounting for spatial spillovers. The relative success in 2014-2020 may suggest that the shift towards a more place-based policy approach was more effective than the narrower focus on convergence in the earlier period, or it may highlight the policy's limitations during economic crises such as the 2008 financial crisis and the eurozone crisis.

The remainder of this thesis is outlined as follows: Section 2 gives some background and context to the EU Cohesion Policy, Section 3 provides the theoretical framework and Section 4 gives an overview of previous research on the matter. Section 5 then outlines the empirical approach, Section 6 describes the data and Section 7 presents the results. Finally, Section 8 concludes by discussing policy implications and future research.

2

EU Coheion Policy

The European Union's Cohesion Policy is a fundamental component of the EU's strategy to promote economic, social, and territorial cohesion among its member states. Established as a mechanism to reduce developmental disparities between EU regions, this policy aims to foster harmonious development throughout the Union, enhancing economic integration and ensuring that the benefits of economic growth are distributed equitably across all regions.

The origins of the Cohesion Policy can be traced back to the 1957 Treaty of Rome, which emphasized the need to reduce disparities between regions and address the underdevelopment of less favored ones. However, it was not until the significant reforms in 1989 following the accession of Greece, Spain and Portugal that investments in regional policy began to form a substantial potion of the EU budget. These changes marked the beginning of what is now known as the modern Cohesion Policy (European Union, 2008). Subsequent treaties have further refined the Cohesion Policy: The Maastricht Treaty of 1992 introduced the Cohesion Fund (CF), and during this period, the resources for structural and cohesion funds doubled and The Lisbon Treaty 2007 emphasized "greater social, economic and territorial cohesion" as a fundamental goal .

Financially, the Cohesion Policy is supported through the Structural and Investment Funds, comprising the Europe and Regional Development Fund (ERDF), the Cohesion Fund (CF), and the European Social Funds Plus (ESF+) along with the Just Transition Fund (JTF). These funds are targeted to support socio-economic development in less developed EU regions and cities, enhance environmental sustainability and transport infrastructure in poorer EU countries, and foster job creation and social inclusion in the EU (European Union, 2008). The funds are managed through multi-level governance model and is a partnership between the European Commission, the member states and local governments and organizations (Fratesi, 2024).

The Cohesion Policy is organized into seven-year programming periods, each characterized by specific objectives that has evolved over time. Within these periods, regions are classified at the NUTS2 (Nomenclature of Territorial Units for Statistics) level into various categories based on their development status. Less developed regions, identified by a GDP per capita in purchasing power parity (PPP) below 75% of the EU average, receive more focused funding to aid in their development and convergence with their more developed counterparts. While this rule has remained throughout, the other objectives above this threshold have gone from encompassing a broad set of objectives to being more streamlined, leading to more consistent objectives in recent programming periods (Fratesi, 2024).

During the 2007-2013 programming period, there was two main objectives: "Convergence" for regions below the 75% threshold, and "Regional Competitiveness and Employment" (RCE). Following the 2004 EU-25 enlargement of eight Eastern European countries along with Cyprus and Malta, the average GDP per capita fell compared to the average in the EU-15 countries. Consequently, some regions previously eligible for support became above the 75% threshold solely due to changes in measurements. These regions received "Phasing-Out" (PO) support from the Cohesion Fund (EUR-lex, 2006). Similarly, regions covered by objective status in the 2000-06 period but not in the 2007-13 period, even within the EU-15, recieved "Phasing-In" (PI) support through the RCE-objective. In the 2014-20 period, the categories were more easily defined: "Less Developed" (<75%, corresponding), "More Developed" (GDP per capita > 90% of EU average) and a new "Transition" category (GDP per capita between 75% and 90% of the EU average) for regions that have become more competitive but still require some targeted support. Additionally, in both periods, member states with a GNI/head below 90% of the EU25/EU27 average also received funding from the Cohesion Fund European Commission (2014). [1]

The eligible regions below the 75% threshold and non-eligible regions above the 75% threshold are depicted in Figure 2.1. Both maps illustrate a clear core-periphery pattern, with mainly Eastern Europe and most of Southern Europe being eligible for funding, while most of North-Western Europe is not. Several regions have experienced a change in status: essentially all of Eastern Germany, parts of Spain, Greece and the UK, and some regions in Eastern Europe have transitioned away from eligible status in the later period. Conversely, two regions, Basilicata in Italy and Kentriki Makedonia in Greece transitioned the other way around.

[1] Member states below this threshold largely reflect the same regions being eligible for the Convergence objective, however some regions within these countries are not. See Section 6 for a further discussion on what this implies for the study.

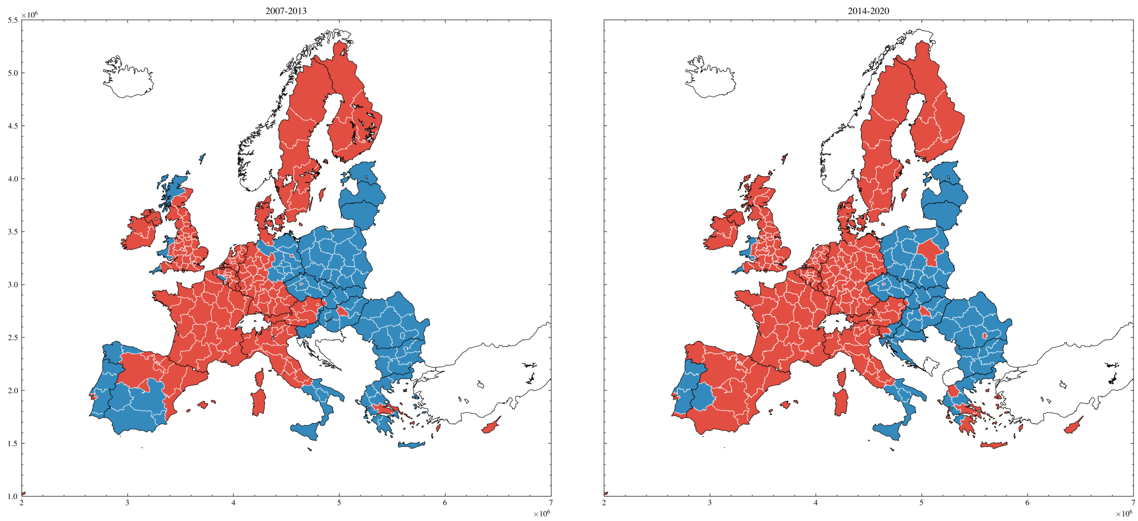


Figure 2.1: Objective Regions Below 75% (in Blue) and Non-Objective Regions Above 75% (in Red) in the EU-27 Countries in 2007-13 and the EU-28 Countries in 2014-20. ***Note:*** *Islands Are Not Depicted in the Maps, Including the French Overseas Departments (French Guiana, Mayotte, Réunion, Martinique, and Guadeloupe), the Two Autonomous Portuguese Regions (Azores and Madeira), and Spain's Canary Islands. All of Which Except Madeira and Canary Islands Are Convergence-Objective Regions in Both Periods.*

The picture of the development during this period is twofold. In the most recent 9th Cohesion Report, the European Commission (2024) described a significant convergence, particularly in the two decades following the 2004 enlargement. Income per capita in Central and Eastern Europe as a whole has increased from 52% of the EU average in 2004 to nearly 80% in 2024. Conversely, many regions, especially in the Soutern Member States, have experienced a gradual divergence, exacerbated by the financial crisis of 2008.

To illustrate the relative development over time between eligible and non-eligible regions, Figure 2.2 uses 2007 as a baseline (GDP per capita in 2007 = 0). The plot shows that regions treated under the "Convergence Objective" and classified as "Less Developed" have seen the most significant growth from 2007 to 2020, while non-eligible regions have experienced moderate growth. Regions switching between eligibility statuses show varied trends: those transitioning from eligible to non-eligible have grown more than non-eligible regions, while those moving in the opposite direction have experienced negative growth (note that this is only two regions in Italy and Greece). This pattern aligns with expectations, as regions losing their objective status typically surpass the 75% threshold, whereas regions gaining objective status fall below it.

For further insight, a second plot focuses on specific geographical groups within the eligible regions: Eastern, Southern, and North-Western Europe. Eastern Europe has experienced the highest growth, followed by North-Western countries. In contrast, Southern Europe has seen minimal or even negative growth on average.

This uneven distribution of growth raises concerns that the benefits of potential treatment effects may be largely confined to Eastern and North-Western Europe, with Southern Europe not experiencing similar advantages.

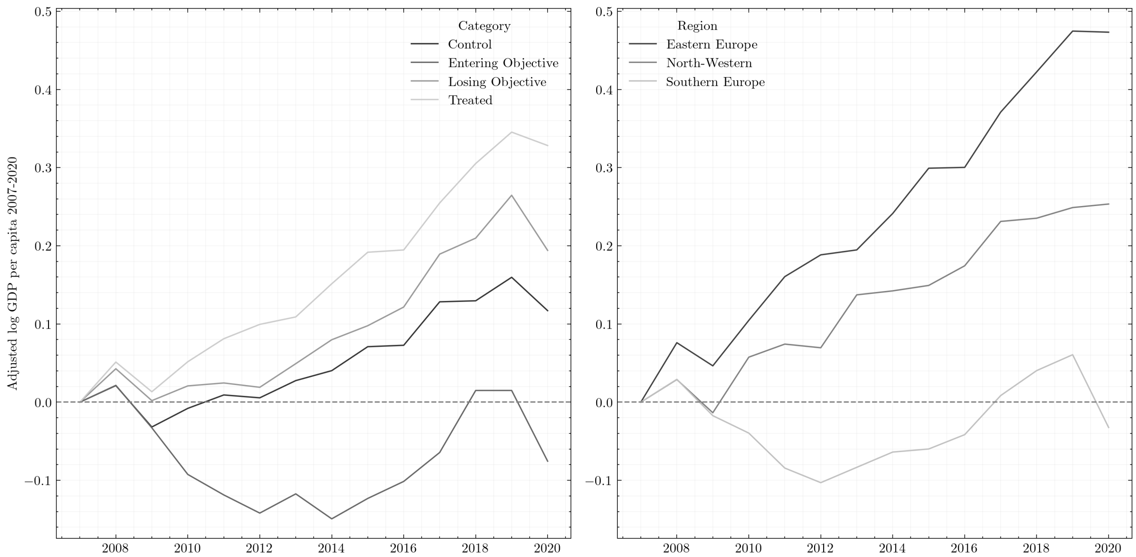


Figure 2.2: Development in GDP per Capita (PPS) Between Eligible Regions and Geographical Groupings, 2007-2020, Log Change Relative to 2007. ***Note:*** *The Member State Groupings Is Based on EU's Definition by Geographic Area.*

3

Theoretical Framework of Regional Policy and Growth

The effectiveness of regional policies in promoting economic growth hinges on a critical examination of whether such policies are necessary and what they aim to achieve. The justification for implementing regional policy derives from an understanding that market forces alone may be insufficient, particularly under the neoclassical assumption of perfect information and optimal market functioning. In reality, significant disparities often persist due to market or institutional failures, necessitating targeted interventions to enhance equity and efficiency across regions, thus necessitating the need for regional policies.

Fratesi (2024) suggests that the justification for implementing regional policies hinges on satisfying three critical considerations: i) the spontaneous outcomes of the market are found to be dissatisfying in at least one aspect, such as leading to unequal regional development or persistent income disparities, ii) standard macroeconomic policies prove inadequate in addressing the spatial disparities created by market forces, which may fail to effectively target the unique challenges faced by certain regions, necessitating more focused interventions and iii) there exist regional policies that have the potential to improve the situation, specifically designed to address the geographical, economic, and social characteristics of different regions.

Various economic theories provide different perspectives on regional growth and the role of policy. These theories help us comprehend the dynamics of regional development and the potential impacts of targeted interventions.

3.1 Economic Theories of Regional Growth

The Neoclassical Growth Theory (NGT) is the most fundamental framework when exploring determinants of economic growth. It posits that all regions should converge toward a steady state of growth, driven by capital accumulation, labor mobility, and technological advances. This theory suggests that poorer regions will naturally catch up to richer ones due to diminishing returns on capital and labor migration to more developed regions (Barro and Sala-i Martin, 1992). This means that as economic integration promotes convergence, there would not be no need for regional policy, as there would be a stable spatial equilibrium of no regional disparities. Instead, policies should solely aim to reduce rigidities that slow this process down, such as barriers to trade (Fratesi, 2024). However, in less stringent models within the NGT, growth rates and the steady states depend on specific features specific to each economy, such as the quality of institutions, which implies that regions with similar characteristics will converge to locally stable steady states, so called "convergence clubs" (Barro and Sala-i Martin, 1992). In this view, regional policies could aim to facilitate conditions needed for regions to move to another 'higher' club.

Contrasting this, the literature on New Economic Geography (NEG), primarily developed by Krugman (1991), highlights how economic activities cluster in 'core' areas, creating agglomeration economies at the expense of peripheral areas. These clusters attract more investment and skilled workers, potentially leading to a divergence, not convergence, across regions. The increased gap between the core and peripheral regions is also supported by endogenous growth theory and innovation economics (Pieńkowski and Berkowitz, 2016). In this view, a the stable spatial equilibrium could be a situation of persistent regional disparities, and thus regional policies aimed to minimize interregional inequalities in less developed and peripheral regions could be desirable to counteract the market forces working towards divergence. However, this will not necessarily maximize the total growth - posing a trade-off between efficiency and equity.

Navigating the trade-offs between equity and efficiency is central a central challenge to the design of regional policies. These trade-offs are influenced by whether regional growth is viewed as generative or competitive, as illustrated by Richardson (1973). In a generative growth model, the development of one region enhance the overall economy, potentially leading to benefits for neighboring regions via positive spillovers. On the other hand, competitive growth models propose that regions compete for a limited pool of resources, implying the presence of negative spillovers - that the growth of one region may occur at the expense of another. While the former poses no trade-off between equity and efficiency, the trade-off in the latter does. With the presence of positive spillovers/externalities, regional policies could increase the overall income levels, but with negative spillovers, the overall benefit is less than the increase seen in the target region, as the policy will achieve growth in the targeted region but reduce it elsewhere

3.2 Place-Based Policies

Whilst historically, regional policies has focused on equity, during economic downturns when resources are scarce, the emphasis shifts towards increasing efficiency

(Fratesi, 2024). This shift can be seen with the development of the EU Cohesion Policy that was originally created with the purpose of reducing regional differences in development, but for the 2000-2006 and 2007-2013 programming periods it was criticised for its narrow focus on convergence (Bachtler and Gorzelak, 2007). More recently, during the recent programming period of 2014-2020, the focus have shifted somewhat from redistribution to investment and increasingly improve the overall competitiveness of the EU as a whole. This new focus highlight the increased relevance of new so called *place-based* theories that suggest that it is possible to overcome the equity-efficiency trade-off (Fratesi, 2024).

This approach has been supported by many recent contributions in regional science, where the key idea is that policies are tailored to the unique economic and social characteristics of each region, aiming to unlock regions underlying potential while minimizing adverse spillovers (Barca, 2009). One of the main theoretical basis for such policies is that the agglomeration externalities can be exploited by leveraging local capabilities and resources, that not only drives regional development but also supports broader economic growth. This theoretical basis asserts that by focusing on enhancing local conditions through specialized, region-specific policies, regions can develop unique competencies that contribute to a mode balanced overall economic landscape (Neumark and Simpson, 2015). *Smart Specialisation Strategies* (S3), prominently featured in the 2014-2020 EU programming period, exemplify this approach by encouraging regions to identify and invest in their unique areas of competitive advantage. The goal of S3 is not just to foster local innovation, but to create a network of complementary capabilities across regions that collectively boost the EU's global competitiveness (Fratesi, 2024). However, it is important to recognize that the research on the long-term economic sustainability of these policies is not conclusive and is still evolving (Neumark and Simpson, 2015).

4

Previous Research on the EU

The existing literature on the impact of EU funds on economic growth is mixed. Dall'Erba and Fang (2017) conducted a meta-analysis on 17 studies and estimated an average estimate of growth elasticities close to zero at 0.174, ranging between -7.6 to 6.3. One plausible reason for the broad range of findings can be attributed to methodological differences. Many studies attempting to measure the impact of European cohesion policy employ econometric techniques based on the neoclassical growth model, rooted in empirical work on regional growth and convergence (Pieńkowski and Berkowitz, 2016). Early studies by Sala-i Martin (1996); Boldrin and Canova (2001) utilized such cross-sectional regressions and found no discernible impact from EU's *Structural Funds Programme*, ultimately deeming it largely ineffective.

However, as noted by later studies, this approach may lead to endogeneity and yield unreliable, biased estimates. One endogeneity issue is due to reverse causality, as the allocation of structural funds is closely correlated with indicators of economic growth (Becker et al., 2012; Mohl and Hagen, 2010). Within the neoclassical framework, regions with a lower GDP per capita are expected to growth independently of EU funds, and since the criteria for fund allocation is based on the relative GDP per capita (in PPS), regions with greater potential for economic growth are more likely to receive funds. Another endogeneity issue is omitted variables. For example, regions with structural issues may continue receiving funds because these underlying problems inhibit growth, not necessarily due to the effectiveness of the funds themselves. This leads to a spurious correlation between funding and economic performance, as these factors are not included in the analysis, thereby biasing the results (Fidrmuc et al., 2024). Dall'Erba and Fang (2017) noted in their review that most studies has tended to ignore these endogeneity issues, thereby obscuring the true causal effect of the policy.

More recent studies has tried to tackle this endogeneity by the means of quasi-experimental methods, such as synthetic control methods (Barone et al., 2016) and instrumental variables (IV)-estimation (Fidrmuc et al., 2024). Most notable however, is the regression discontinuity design (RDD) which has been employed by several studies to exploit the eligibility threshold of the objective regions (Becker et al., 2010, 2013, 2018; Pellegrini et al., 2013; Cerqua and Pellegrini, 2018; Gagliardi and Percoco, 2017; Percoco, 2017; Giua, 2017; Crescenzi and Giua, 2020). This has been done in particular to compare growth in less developed (Objective 1/Convergence objective) regions that receive more substantial support from the Cohesion Policy ('treated group') with regions that do not receive any support from the Cohesion Policy ('control group'). This method shows an important discontinuity of regional GDP growth at the threshold point corresponding to the border between the eligible and non-eligible regions (75% of the average EU GDP per capita), which clearly shows the impact of Cohesion Policy 'treatment'.

Pellegrini et al. (2013) used a dataset covering two programming periods between 1994-2006, identifying positive albeit modest effects of the Objective 1 interventions on growth. Similarly, Becker et al. (2010, 2013) employed data covering the years from 1989 to 2006, and further expanded this dataset to include up to 2013 in a subsequent study (Becker et al., 2018). These studies all found an overall positive influence on GDP growth, although at different magnitudes. In Becker et al. (2018), they noted that the policy is effective in the short-term, but not as much in the long-term. Giua (2017) and Crescenzi and Giua (2020) applied a spatial RDD (comparing outcomes in areas just inside and outside a geographical treatment boundary) to municipalities and regions near the borders of funded and non-funded areas, identifying heterogeneous growth and employment effects, successfully in German regions, but less so in Italy and Spain. Gagliardi and Percoco (2017) noted significant benefits in rural regions near urban centers, highlighting the spatial variability in the effectiveness of EU Cohesion Policy. In Table 4.1 the previous research applying RDD on the EU Cohesion Policy and the sample and design is summarized. It is notable that the majority of studies have focused on earlier periods, particularly on the 2000-2006 period. Only one study has extended its analysis to include the later period of 2007-2013, while none have yet investigated the most recent 2014-2020 period.

Another reason for the mixed and weak overall results on the impact of EU funds is the oversight of spatial spillovers, i.e., the broader economic effects that EU-funded projects can have beyond the targeted regions (Pieńkowski and Berkowitz, 2016). Investments in one area may benefit neighboring regions or even wider geographical areas due to the interconnected nature of the EU's economy, where goods, services, labor, and capital flow relatively freely across borders. Recognizing these spillover effects is crucial for accurately assessing the full impact of Cohesion Policy, as they can amplify or negate the perceived effectiveness of these investments. While some studies find positive impacts of these funds both in the regions where they are directly invested and in adjacent areas (Mohl and Hagen, 2010; Fidrmuc et al., 2024), others do not find significant benefits or even suggest negative effects (Breidenbach et al., 2019). Fidrmuc et al. (2024) found that the favorable, although weak, effect took place more in nearby regions rather in the recipient region.

Table 4.1: Previous RDD research on the EU Cohesion Policy

Author	**Method**	**Period**	**Countries**
Pellegrini et al. (2013)	Sharp RDD	1994-2006	EU-15
Pellegrini (2016)	Sharp RDD	1994-2006	EU-15
Becker et al. (2010)	Fuzzy RDD	1989-2006	EU-15
Becker et al. (2013)	Mixed Fuzzy RDD	1989-2006	EU-15
Becker et al. (2018)	Fuzzy RDD	1989-2013	EU-25
Giua (2017)	Spatial RDD	1988-1999	Italy
Crescenzi and Giua (2020)	Spatial RDD	2000-2006	EU-15
Percoco (2017)	Fuzzy RDD	2000-2006	EU-15
Gagliardi and Percoco (2017)	Fuzzy RDD	2000-2006	EU-15

5

Empirical Approach

To assess whether the EU Cohesion Policy lives up to its goal and effectively boosts regional performance, I will employ a Regression Discontinuity Design (RDD). This approach leverages the eligibility for Cohesion Policy funding - set at 75% of the EU average GDP per capita - as a quasi-experimental cutoff to discern the policy's impact on regional growth. RDD is particularly well-suited for this analysis as it capitalizes on the natural experiment created by the policy design. Specifically, it explores whether regions that marginally qualify for Cohesion Policy funding exhibit significantly different economic outcomes compared to those that narrowly miss qualification. The intuition of RDD in this context is that the discontinuity around the threshold can be exploited to create counterfactuals: by focusing on regions around the critical eligibility threshold of 75% GDP per capita relative to the EU average, this analysis seeks to understand the effects of policy interventions at the margin - where similar regions may experience vastly different policy treatment due to slight differences in their economic status. For example regions just below the threshold at 74.99% and just above at 75.01% are likely more comparable than regions located far away.

Moreover, recognizing the interconnected nature of regional economies, the RDD approach is extended by integrating spatial econometric techniques. This enhancement is crucial to capture not only individual regional treatment effect but also the indirect effects of the policy - specifically, regional spillover effects. Regional economic growth is generally seen as highly interdependent, influenced by (1) neighbouring region characteristics, (2) the spatial connectivity structure of regions, and (3) the strength of the spatial dependence (LeSage and Fischer, 2008).

In the EU - a single free market with free trade in goods and services and unhindered mobility of labor and capital - Cohesion Policy funds are likely to impact not only on the economy of the region receiving funds but also neighboring regions. For example, Objective transfers could used to finance public infrastructure can generate not only local effects on the treated regions but also spillovers to neighbouring regions. This is even expressed as an explicit goal to "support national, regional and local, cross-border and urban mobility" and to further develop the trans-European transport network (EUR-lex, 2021, p.4). This notion is also crucial from a theoretical standpoint, aligning with insights from new economic geography, which emphasize the role of spatial interactions and agglomeration effects in shaping regional economies. These theories highlight how economic activities in one region can spill over and influence neighboring areas [1], creating complex spatial dynamics that shape regional development patterns. Despite the the clear policy importance and theoretical relevance, estimating spillovers have not been comprehensively explored in previous RDD-literature on the Cohesion Policy. [2]

Beyond the intrinsic interest in exploring spatial spillovers, their consideration is also important from a methodological standpoint. The presence of spatial spillovers would violate the *non-interference* assumption (Imbens and Rubin, 2015; Cornwall and Sauley, 2021) leading to downward biased estimates of the average treatment effect. Positive spillovers, for instance, can reduce the observed difference in growth rates between the treated and untreated regions, complicating the interpretation of treatment effects (Becker et al., 2010). Spatial econometric models also help detect and account for spatial autocorrelation, a phenomenon where the similarity in values among geographical units can skew the results.

5.1 Regression Discontinuity Design

The Regression Discontinuity Design (RDD) hinges on several key methodological considerations: mainly whether to use parametric or non-parametric regressions, choosing between sharp versus fuzzy designs. Following the approach of Pellegrini et al. (2013), this study will utilize a sharp design and both parametric and non-parametric estimation techniques. In a sharp Regression Discontinuity Design (RDD), eligibility for treatment is determined solely by whether the running variable crosses the predefined cutoff point. This setup offers the advantage of a clear causal interpretation, although it requires careful data handling, as discussed in Section 6.

The treatment effect is identified by a binary Objective status, defined as:

$$T_i = \begin{cases} 1 & \text{if } \tilde{x}_i \leq 0 \\ 0 & \text{if } \tilde{x}_i > 0 \end{cases} \tag{5.1}$$

[1]Related regions will be referred as 'neighbours', but do not necessarily mean contiguity-based (sharing a border) relationships, but more general sense of relatedness.

[2]Note that Pellegrini et al. (2013) and Becker et al. (2010) addressed spatial spillovers, but only from a methodological point of view as a robustness check of their main results. Pellegrini et al. (2013) used a spatial lag model, only accounting for spillovers in the dependent variable (economic growth) but not the independent variable (the treatment), and no considerations where thus made as to whether the treatment itself had an impact neighboring regions. They also acknowledges the absence of theoretical framework as a limitation of their study that does not engage with assumptions of regional growth. Becker et al. (2010) did not use spatial econometric techniques at all, only adjusting the selection of control units.

Where i denotes each NUTS-2 region, T_i represents the objective status (the "treatment"), x_i is the running variable, which is the GDP per capita of the region as a proportion of the EU average in the years the rule was determined. The term $\tilde{x}_i = x_i - 0.75x_0$ represents the deviation of the GDP per capita in each region from 75% average x_0 in the threshold years.

To estimate the average causal treatment effect at the threshold without assuming any specific functional form, the non-parametric RDD-estimate can be written as (Angrist and Pischke, 2009):

$$\tau = \lim_{d \to 0} (E[y_i \mid \tilde{x}_i < d] - E[y_i \mid \tilde{x}_i < -d]) = E[y_{1i} - y_{0i} \mid \tilde{x}_i = 0] \tag{5.2}$$

Where $E[y_i \mid \tilde{x}_i < d]$ is the expected outcome for units slightly above the threshold, within a small interval d of the running variable deviation $\tilde{x}_i$, $E[y_i \mid \tilde{x}_i < -d]$ is the expected outcome for units slightly below the threshold, within the same small interval $-d$. The limit $\lim_{d \to 0}$ indicates narrowing the interval around the cutoff $\tilde{x}_i = 0$ (the deviation from 75% of the EU average GDP per capita, where $\tilde{x}_i = x_i - 0.75x_0$) to an infinitesimally small size, ensuring comparisons are made as close as possible to the threshold to minimize the influence of other factors. Lastly, $E[y_{1i} - y_{0i} \mid \tilde{x}_i = 0]$ is the expected difference in outcomes precisely at the cutoff point.

Next, the parametric approach for estimating the RDD is formalized as follows:

$$y_i = \alpha + \tau T_i + \sum_{j=1}^{m} \beta_j \tilde{x} i^j + \sum_{j=1}^{m} \delta_j (T_i \times \tilde{x}_i^j) + \epsilon_i \tag{5.3}$$

Where y_i represents the economic growth, α is the intercept, T_i is a binary treatment indicator as defined in Equation 5.1 with τ capturing the direct effect of the treatment. $\tilde{x}_i$ is the running variable, and $\tilde{x}_i^j$ represents its j-th power, allowing for a polynomial specification. β_j are coefficients for each polynomial term of $\tilde{x}_i$ and δ_j are coefficients for interaction terms between T_i and each polynomial term of $\tilde{x}_i$, enabling the model to capture how the effect of the treatment varies with different levels of $\tilde{x}_i$. ϵ_i is the error term, capturing random deviations not explained by the model.

5.2 Spatial Dependence

In order to address the cross-regional spillovers, it is essential to consider the spatial dependence in the data. Spatial dependence describe how geographical units - such as NUTS2 regions in this study - are interconnected and can influence each other. This concept is somewhat analogous to time-series analysis, which uses Autoregressive (AR) and Moving-average (MA) models to account for temporal dependencies as spatial dependencies in economic data can manifest either through a spatial lag or in the error process. Not accounting for these dependencies can lead to biased and inefficient estimates (Anselin, 1988). To properly handle spatial dependence, spatial models are estimated that incorporate linkages among regions based on a chosen spatial weight matrix.

5.2.1 Spatial Weight Matrix

The assumptions made on the structure of linkages among geographical areas is reflected on the choice of spatial weight matrix, upon which spatial models then can be used to estimate spillovers (Anselin, 1988). [3] This matrix essentially defines the connections between regions, specifying which areas influence each other and to what extent. By selecting appropriate weights, researchers can model different types of regional interactions. For instance, a common choice is to use a contiguity-based matrix where regions sharing borders are assumed to influence each other, or a distance-based matrix that considers all regions within a certain radius as interconnected. For this thesis, both of these matrices are considered. [4]

The Queen-Contiguity is utilized for the simplicity and clarity in defining neighbors as regions that share a border (or a *vertex*). This matrix is effective when policy spillovers are expected to most pronounced between directly adjoining regions. The mathematical representation of a typical contiguity-based matrix, W, is defined as:

$$W = \begin{cases} w_{i,j} = 1 & \text{if } i \neq j \text{ and } i, j \text{ share border or vertex} \\ w_{i,j} = 0 & \text{otherwise} \end{cases} \tag{5.4}$$

Where i and j is the centroid (the geometric center of a region) of regions and w_{ij} denotes the elements of the spatial weight matrix W. An important limitation of the Queen matrix is that it does not account for islands or disconnected regions, which must be taken into consideration.

In contrast, distance-based matrices offer a broader range of interactions. These matrices may use a threshold to determine connectivity or treat all regions as interconnected regardless of distance. The global linkage approach, which does not

[3]The spatial weight matrix is a fundamental advantage in spatial econometrics but also attracts criticism due to the assumptions needed about its form (Gibbons and Overman, 2012). However, as noted by Abreu et al. (2004), choosing not to specify a spatial weight matrix also implicitly assumes a specific spatial structure—that the regions do not influence each other.

[4]One important caveat is that the spatial weight matrix must be exogenous, and time-invariant which precludes using other types of spatial distances such as trade or cultural distances which in practice could be argued to be more realistic (Abreu et al., 2004). For this reason, most spatial weight matrices are based on distance or contiguity, since they are clearly exogenous (Anselin and Bera, 1998).

restrict economic interactions by distance, can be represented as follows:

$$W = \begin{cases} w_{i,j} = 0 & \text{if} \quad i = j \\ w_{i,j} = \frac{d_{ij}^{-2}}{\sum_j d_{i,j}^{-2}} & \text{otherwise} \end{cases} \tag{5.5}$$

Here, $d_{i,j}^{-2}$ is the squared inverse distance between centroids of regions i and j, and the weights are normalized such that the sum of all weights for each row equals to one. This normalization ensures that the influence exerted by all neighboring regions on a given region i is standardized, providing a relative rather than absolute measure of distance. The squared inverse weighting means that the influence of a region is diminishing more steeply with the square of the distance. This approach is beneficial when economic interactions are not strictly limited by proximity and can span broader geographic expanses, thus reflecting more realistically the interconnected nature of modern economies (Kopczewska et al., 2017). [5]

5.2.2 Spatial Models

To effectively distinguish between direct and indirect effect of spatial relationships, the Spatial Durbin Model (SDM) is particularly suited due to its ability to include spatial lags of both dependent and independent variables. The SDM is comprehensive, as it also nests other spatial models, specifically both the Spatial Lag Model (SLM) and the Spatial Error Model (SEM), making it suitable to start with and differentiate between the SDM and other potential models (Fidrmuc et al., 2024).

The modification to incorporate the spatial terms into the parametric model as described in Equation 5.6 is as follows:

$$y_i = \alpha + \tau T_i + \sum_{j=1}^{m} \beta_j \tilde{x} i^j + \sum_{j=1}^{m} \delta_j (T_i \times \tilde{x}_i^j) + \rho(Wy)_i + \phi(WT)_i + \epsilon_i \tag{5.6}$$

Here, $\rho(Wy)_i$ represents the spatial lag of the dependent variable y, indicating how similar outcomes in neighboring regions influence the region i. $\phi(WT)_i$ represents the spatial lag of the treatment variable T, which accounts for the spillover effects of treatments applied in neighboring regions.

[5] The autonomous overseas territories far away from he mainland is excluded because these would inflate the cut-off distances. Also, the economical impact of the nearest EU regions on these territories are likely very limited.

6

Data

6.1 Data Harmonization

The data is composed from several sources (see A.1) with the spatial grid defined by NUTS at level 2. The NUTS classification is a hierarchical system for dividing up the economic territory of the EU, that generally mirrors the territorial administrative division of the Member States. It is divided at four different levels (NUTS 0, 1, 2 and 3) where 0 is the largest at the national level of the member states and 3 is the smallest, typically comprising of small regions or groups of municipalities. One of its explicit purposes is the framing of EU's regional policies where regions eligible for support from cohesion policy has been defined at the NUTS-2 level (Eurostat, n.d.).

However the regions has been adjusted on a regular basis (i.e. 2003, 2006, 2013, 2016 and 2021), and the data is available at different classifications, which means that the data need to be denoted in one single version in order to create a harmonized dataset. This is done using Eurostat's correspondence tables to assign the observations in the programming periods according to one homogeneous NUTS classification, NUTS-2006. See Appendix A for a closer explanation of how these regions are mapped and which regions this concerns. However, a few regions where not possible to map, resulting in a loss of a few regions. In total, the mapping yields a dataset of 271 EU-28 regions for the 2014-20 period and 261 EU-27 regions in 2007-13 period.

6.2 Treatment Variable

The binary Objective treatment variable T_i is determined on whether a NUTS2 region has a GDP per capita in purchasing power parity terms (PPS) is less than 75% of the EU average. For the last two completed programming periods used here, 2007-2013 and 2014-2020, the European Commission computed the relevant threshold of GDP per capita in PPS terms based on the figures for the last three years of data available at the time when the Commission's regulations came out, which correspondingly are 2000-02 and 2007-09 (European Commission, 2017).

The treatment assignment are depicted in Figure 6.1 below, pooled from both periods, to observe how the rule has been implemented, and those that have switched statuses throughout the two periods. The dashed line on the x-axis denotes the 75% rule and we observe that all regions in both periods on paper adheres to this rule.

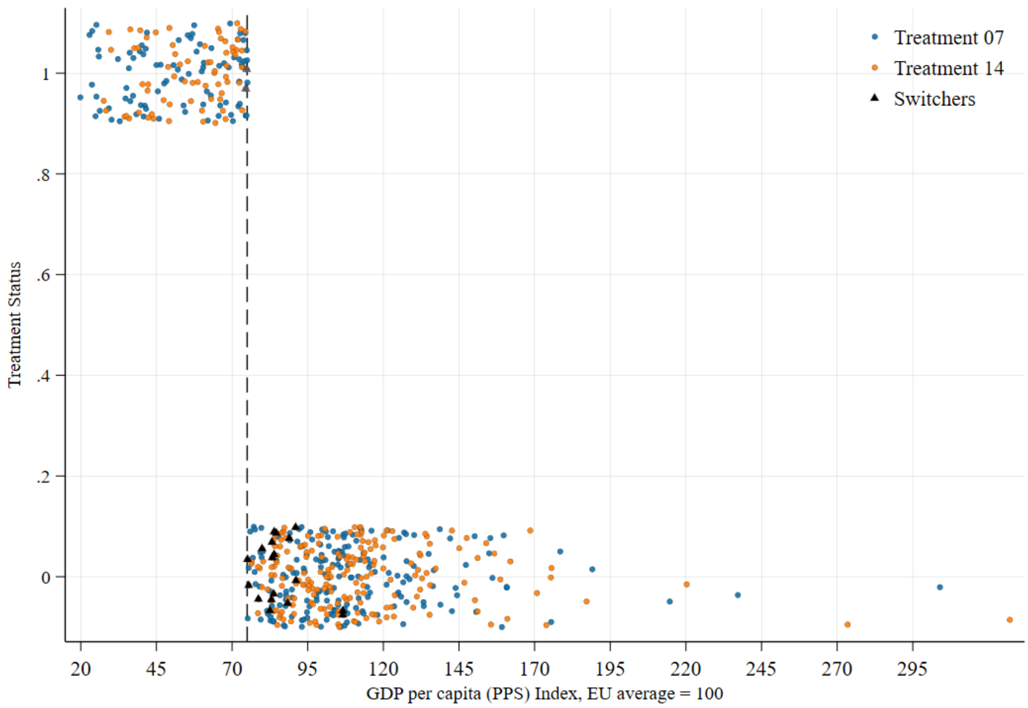


Figure 6.1: Assignment of Treatment Status in 2007-13 and 2014-20. ***Note:*** *The data points are "jittered" to avoid overlap and enhance clarity, the regions can only take a value of 1 if below the threshold or 0 if above.*

However, it is important to consider is how the EU transfers have been allocated in practice. In the Figure 6.2 below, the amount of EU Funds per initial GDP is plotted for both periods. While there is a distinguishable jump at 75% in the amount of funding allocated to the treated regions, it is noticeable that some control regions above the threshold value of 75% does still receive a significant amount of funding despite not being eligible. This is to be expected to some degree, for example the Cohesion Fund finances projects only in member states whose Gross National Income (GNI) per inhabitant is less than 90 percent of the EU average. In the 2007-13 period, this concerned all member states that joined the EU in 2004 and 2007 along with Greece and Portugal. While the eligibility status (below 75%) covers the majority of their territory, a few non-objective regions in these countries received support from the Cohesion Fund. This also concerned the Phasing Out (PO)-regions which received 20% of the Cohesion Fund allocation European Commission (2010).

To conduct a Sharp Regression Discontinuity Design (RDD) and compare the economic performance of "hard financed" regions with "soft financed" regions, a threshold value of per capita aid intensity has been established, following the methodology described by Pellegrini et al. (2013). This approach involves identifying a minimum threshold of EU Funds per initial GDP for treated regions and excluding all non-treated regions that exceed this threshold, thereby minimizing overlap and ensuring that no control regions have received more funding than the treated regions. The thresholds determined are 0.13% for the 2007-13 period and 0.18% for the 2014-20 period. This exclusion criteria imply a removal of 17 regions in the 2007-13 period and 24 regions in the 2014-20 period from the analysis. A discussion of these regions and further information are provided in Table A.3. Naturally, this poses a limitation of this study by potentially omitting valuable data that could influence the overall findings. [1]

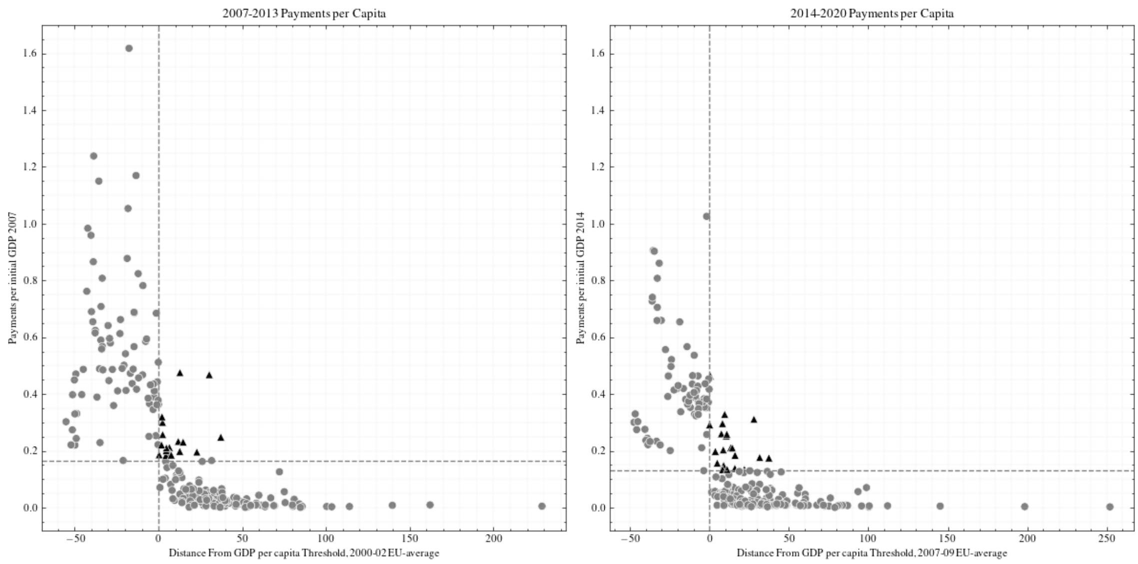


Figure 6.2: Structural Funds Per Initial GDP in the 2007-13 and 2014-20 Programming Periods

6.3 Outcome and Control Variables

The variable of interest is the per capita growth in GDP, measured in purchasing power standards (PPS), from 2007 to 2020 for the EU-28 countries. Regional GDP is technically calculated as the regional Gross Value Added (GVA) plus taxes on products minus subsidies on products. The PPS values are derived using the EUR/PPS conversion rates from AMECO.

Control variables used is initial population, employment share and population structure that could influence the the effect of treatment on growth. Additionally, fixed effects will be utilized to account for unobserved heterogeneity that may

[1]While the total amount of regions excluded compared to Pellegrini et al. (2013) are a few more, the complete dataset here are substantially larger.

vary across both countries and the two funding cycles. Furthermore, in the spatial econometric model, spatial lags is also incorporated.

6.4 Descriptive Statistics

In order to introduce the data, summary statistics is presented for GDP per capita growth across treatment groups of NUTS-2 regions over the two programming periods 2007-2013 and 2014-2020, as well as for the combined period of 2007-2020 in Table 6.1. From 2007-2020, treated regions exhibited a significantly higher growth rate (2.7%) compared to non-treated regions (0.9%), whilst regions that switched treatment status, displayed the lowest mean growth (0.8%) and the highest variability (std.dev 2.1), reflecting the pattern seen in Figure 2.2 or possibly suggesting a negative impact of changing status. The growth differential between treated and non treated regions was notable in the 2007-13 period, with treated growing at 1.9% compared to only 0.51% for non-treated regions. The 2014-20 period shows an even larger disparity in growth rates, with treated regions averaging 3.13% growth versus 1.17% for non-treated regions, although smaller in relative terms. In 2007-13 there was a notably high variability (std dev 2.54) among treated regions, possibly reflecting crisis regions experiencing negative growth.

Table 6.1: Summary Statistics and Naive Estimates of GDP per capita growth.

Period	Status	Mean	Δ Mean	Std	N
2007-2020	Non-Treated	0.907		0.856	166
	Treated	2.669	1.762 (0.2357)	1.889	68
	Switchers	0.836		2.148	27
2007-2013	Non-Treated	0.514		1.369	181
	Treated	1.900	1.386 (0.3008)	2.535	80
2014-2020	Non-Treated	1.170		1.265	200
	Treated	3.131	1.961 (0.2466)	1.904	71

Note: Δ Mean represents the difference in average annual GDP per capita growth rates between the treated and non-treated regions. Standard Error (SE) of this difference in paranthesis, calculated using the formula: $SE(\Delta) = (s_t^2/n_t + s_c^2/n_c)^{1/2}$, where s denotes the standard deviation and n the sample size for each group.

Furthermore, Table 6.2 compares the treated and non-treated with respect to different variables at the initial year of both programming periods. Non treated regions are generally more populated than the treated ones and are naturally both richer and more productive. Non-treated regions also have higher employment share and have a somewhat higher median age than treated regions.

Table 6.2: Summary Statistics: Pre-Treatment in Both Periods

		Treatment	
Period	**Variable**	**1**	**0**
2007	Population (Thousands of inhabitants)	1764.745	1903.127
	GDP per capita (PPS)	16683.742	29426.314
	Productivity (GDP per worker, PPS)	39473.301	48938.481
	GDP Index (EU-27 =100, PPS)	57.164	112.283
	Employment Share	58.110	66.019
	Population Structure (Median Age)	36.101	40.884
2014	Population (Thousands of inhabitants)	1722.733	1993.253
	GDP per capita (PPS)	18091.228	30681.246
	Productivity (GDP per worker, PPS)	43368.126	52881.908
	GDP Index (EU-28 =100, PPS)	54.939	111.986
	Employment Share	58.732	66.046
	Population Structure (Median Age)	36.335	40.701

Note: GDP index (EU-27/28) is the data upon which the eligibility rule where decided from the DG Regio database, while GDP per capita (PPS) is from Cambridge Econometrics used to calculate the growth variable.

7

Results

This chapter presents the main findings from the empirical analysis. The RDD strategy will closely follow the methodologies outlined by recommendations of Imbens and Lemieux (2008); Lee and Lemieux (2010) and Jacob et al. (2012). Concerns specifically relevant to the EU Cohesion Policy draws upon previous research by mainly Pellegrini et al. (2013) and Becker et al. (2010, 2018). First, the main RDD analysis is conducted that involves graphical analysis to visually asses the discontinuity at the eligibility threshold and then estimation of the treatment effect using both parametric and non-parametric methods. This analysis is performed separately for each of the two programming periods. To ensure robustness, sensitivity analyses are conducted and the validity of the RDD strategy is evaluated, ensuring that it meets the necessary assumptions for a credible causal inference.

Finally, the analysis is then extended by investigating the spatial dependence in the data and integrating spatial econometric techniques into the RDD framework as suggested by Cornwall and Sauley (2021). By employing a Spatial Durbin Model (SDM), not only the direct effects of the policy can be captured, but also the indirect effects through the spatial linkages between regions. Through these methods, this chapter will detail the outcomes of the policy interventions, highlighting the differential impacts on treated versus non-treated regions.

7.1 Main RDD Analysis

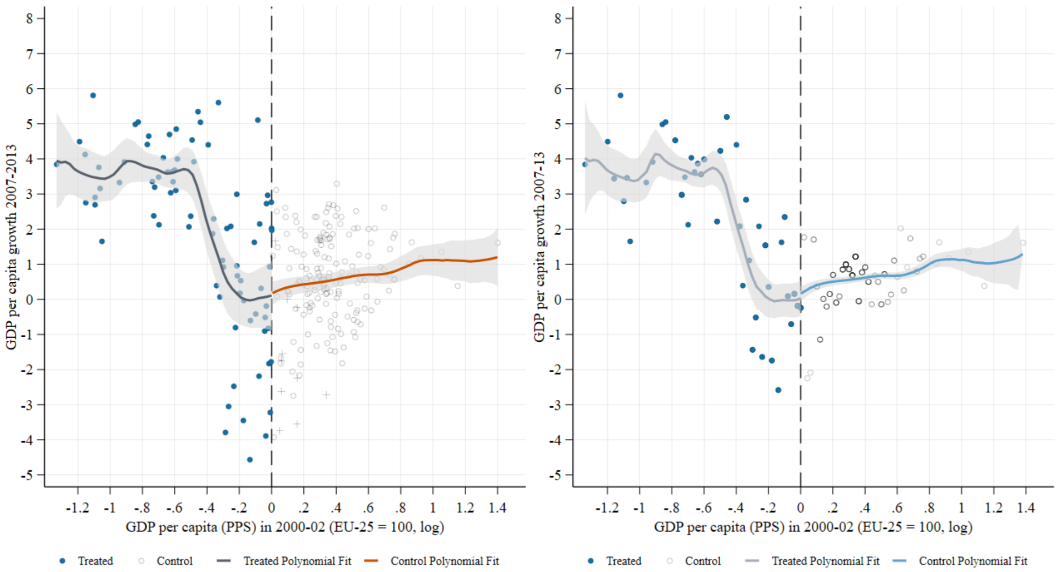
As is conventional within the RD-literature, the analysis starts with a graphical representation to depict the relationship between the outcome variable (average annual growth growth rate of per capita GDP in PPS) and the running variable (the level of GDP per capita in PPS, EU-25/27=100). This approach aims to determine whether there is evidence of a discontinuity, a "jump", at the cutoff. The absence of visual evidence for such discontinuity, would suggest that it is unlikely that more complicated statistical models will yield significant treatment effects (Lee and Lemieux, 2010).

Figure 7.1, illustrates this relationship for the periods 2007-2013 and 2014-2020, with the non-treated regions depicted on the LHS of the threshold value and treated regions at the RHS with a distance from the threshold of $\tilde{x} = x_i - 0.75x_0$. Following Pellegrini et al. (2013), this is depicted with a non-parametric, flexible polynomial regression model, separately estimated in both sides of the cut-off point, together with 95 percent confidence interval bands. Superimposing flexible regression lines is beneficial as it does not assume any specific parametric form for the relationship between the treated and control units, and provides a visual sense of the amount of noise in the data (Jacob et al., 2012). A logarithmic scale is used to reduce the significant skewness and stabilize the variance in the distribution. Crosses in the left figures indicate the observations that received "hard financing" despite not being formally eligible according to the 75% rule. The right graphs are showing the corresponding relationship where these regions are excluded and in bins of 2% in order to help smoothing the the data and highlight the underlying patterns more distinctly (Imbens and Lemieux, 2008).

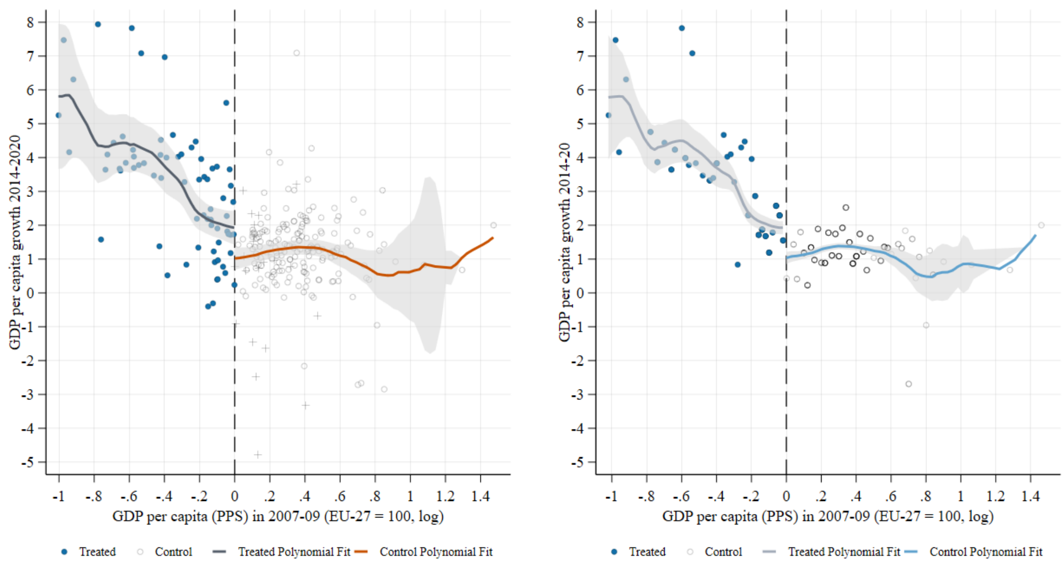
The higher growth rates of treated regions is clearly visualized in both periods, as previously indicated using the naive estimator of the difference of the average annual growth rate between treated and non-treated regions in Table 6.1. The treated regions also exhibit considerably greater dispersion among the treated regions compared to the control regions.

Most importantly, the non-parametric regression line shows a small but distinct negative jump from treated to non-treated regions in the 2014-20 period of what looks to be around 1%. However, no such jump is seen in the 2007-13 period. The polynomial fits indicate a steep downward slope left of the cutoff in both periods, suggesting a strong convergence pattern. In the 2007-13 period, the curve that is relatively flat at the outset but then steeply declines as it approaches the cutoff, indicating a non-linear relationship. The confidence interval is consistently quite wide throughout, particularly at the cutoff, where significant negative growth is observed in many regions. In the 2014-20 period, the confidence intervals suggest less uncertainty around the threshold.

On the control side, to the right of the threshold, there is a relatively flat trend, but slightly upward-sloping as it moves further away from the threshold in the 2007-13 period. In the 2014-20 period, the trend is similar, but there is considerable uncertainty further from the threshold, likely due to the sensitivity of a few individual regions with very high GDP per capita. This causes the polynomial fit to exhibit erratic behaviours, possibly indicating the need for smaller bandwidth or different kernel choices. In general, the findings so far indicates a jump of approximately the same magnitude as (Pellegrini et al., 2013) using the same approach in 1995-2006. However, the steeper negative relationship among the treated regions are much more pronounced here in both periods, which is likely due to the strong convergence pattern of the Eastern European countries.



(a) 2007-2013



(b) 2014-2020

Figure 7.1: Non-Parametric Flexible Polynomial Regression Model in Both Programming Periods. ***Note:*** *The right graphs display the averages of GDP per capita growth, organized into equally sized bins of 2%. In the left graphs, non-compliers in the control group are marked with a '+' and are excluded from the right graph.*

7.1.1 Non-Parametric Estimates

When estimating the treatment effect, one can make use of both parametric and non-parametric approaches, each balancing precision and bias differently. Parametric estimates utilizes the entire dataset, which increases precision but carries a risk of bias due to potentially inaccurate model specifications. In contrast, non-parametric methods focus on data subsets near the cutoff, sacrificing more precision to achieve a more accurate specification of the functional form and thus reduce bias in the estimates (Lee and Lemieux, 2010).

In the Table 7.1 below, the non-parametric estimates is presented using a local linear regression approach. Following Pellegrini et al. (2013), the analysis involves first selecting an optimal bandwidth for the regression, which is crucial for balancing the bias and variance, using a one common MSE-optimal bandwidth selector. Additionally, the sensitivity pf the estimates are evaluated by using different kernels - Triangular, Epanechnikov and Rectangular, since different kernels distribute the weights, or the influence each data point has on the estimation at a particular target point. Similar to Becker et al. (2010, 2013), the standard errors are clustered at the country level to account for potential correlations within each country. This clustering is essential to address shared economic policies, cultural factors, or institutional similarities that might influence the estimates.

As anticipated from the graphical analysis in Figure 7.1a, during the 2007-13 period, the estimates are small and insignificant, indicating a lack of treatment effect during this period. The estimates is small and range between almost zero for the conventional estimates and the bias-corrected estimates are approximately 0.2.

In contrast, the 2014-20 period yields larger and (weakly) significant estimates, possibly indicating a treatment effect. Note that the negative estimates indicate that the GDP growth drop when shifting to the control group, conversely meaning that there is a GDP increase when moving from the control group to the treatment group. Therefore, negative estimates should be interpreted as indicating positive effects of the treatment. Specifically, the conventional estimates are approximately 1.4 and bias-corrected is 1.6, meaning that the latter approach suggest a slightly stronger effect. Robust estimates are not significant for the Triangular and Epanechnikov kernels.

When comparing the estimates depending on kernel, the estimates are consistently lower for the triangular kernel while highest for the rectangular. This patterns suggest that the Triangular kernel, giving more weight to data points close to the cutoff, might be capturing a less pronounced treatment effect. In contrast, the Rectangular kernel, treating all data points within the bandwidth equally, could be incorporating broader variations across the dataset, leading to higher estimates.

Table 7.1: Non-Parametric Estimates Using Different Kernel Types in 2007-2013 and 2014-2020.

	(1) Triangular	(2) Epanechnikov	(3) Rectangular
		2007-2013	
Conventional	0.000919	-0.0143	0.00916
	(1.280)	(1.318)	(1.404)
Bias-corrected	-0.223	-0.200	-0.226
	(1.280)	(1.318)	(1.404)
Robust	-0.223	-0.200	-0.226
	(1.457)	(1.478)	(1.533)
		2014-2020	
Conventional	-1.274	-1.416*	-1.583*
	(0.823)	(0.853)	(0.876)
Bias-corrected	-1.414*	-1.611*	-1.670*
	(0.823)	(0.853)	(0.876)
Robust	-1.414	-1.611	-1.670*
	(0.986)	(1.005)	(0.988)

Note: Clustered standard errors at the country level in parentheses, $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Negative estimates indicate that the GDP growth drop when shifting to the control group, conversely meaning that there is a GDP increase when moving from the control group to the treatment group. Therefore, negative estimates should be interpreted as indicating positive effects of the treatment. Conventional estimates use standard regression, bias-corrected adjust for potential overfitting of the model, and robust estimates account for heteroskedasticity and more complex error structures.

To further investigate the sensitivity of the (weakly) significant estimates in the 2014-20 period, different bandwidths is tested by decrease and increase the bandwidth compared to the optimal threshold obtained above. Also, a two different MSE-optimal bandwidth selectors (MSETWO) - below and above the cutoff - is tested to examine if the estimates vary significantly with adjustments in the bandwidth placement. The results of the sensitivity analysis are presented in Table 7.2. The general pattern is that the estimate decrease and becomes insignificant with a wider bandwidth. This indicate that while it can provide a more comprehensive view of the treatment effect over a larger sample, it also incorporates more variability and potentially irrelevant data that dilute the localized impact of the treatment observed near the cutoff. Interestingly, the msetwo bandwidth selector suggest a lower treatment effect but a higher statistical significance.

To evaluate the influence of the excluded regions, the last row present the bias-corrected estimates for the one-common optimal bandwidth selector using the entire sample. While the magnitude of these estimates varies—appearing both higher and lower compared to the results presented in row 5 in Table 7.1 depending on the kernel used—the statistical significance is consistently higher. Since the excluded regions are exclusively from the control group, it is probable that these regions have experienced relatively poorer GDP per capita growth. This underperformance is logical considering that most of these regions are located in Southern Europe (see Table A.3), suggesting that their exclusion might underestimate some of the true treatment effects of the regional policies.

Table 7.2: Non-Parametric Estimates Over Different Bandwidths and Kernels.

Bandwidth	(1) Triangular	(2) Epanechnikov	(3) Rectangular
15	-1.083	-1.323*	-1.551**
	(0.791)	(0.784)	(0.740)
25	-1.471**	-1.491**	-1.306**
	(0.633)	(0.638)	(0.656)
35	-0.902	-0.781	-0.546
	(0.603)	(0.607)	(0.632)
45	-0.758	-0.674	-0.582
	(0.602)	(0.609)	(0.622)
MSETWO	-1.290**	-1.399**	-1.543***
	(0.564)	(0.557)	(0.555)
MSERD⋆	-1.577**	-1.590**	-1.413**
	(0.652)	(0.644)	(0.682)

Note: Clustered Standard errors at the country level in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ⋆ Refers to the full sample.

In summary, the combined results corroborate the graphical analysis: there is no significant policy effect in the 2007-13 period, but indications of an effect in the 2014-20 period, with an estimate of approximate 1.5 percentage points. The absence of a discernible treatment effect during 2007-2013 aligns with the findings of Becker et al. (2018), who observed that the impact on GDP growth for the 2000-06 and 2007-13 programming periods was notably smaller compared to the entire 1989-2013 span. Their analysis suggests that the effects of transfers diminished during the crisis period, particularly impacting per-capita income in countries most affected by the crisis. Although Becker et al. (2018) do not isolate the 2007-13 period in their estimates, the larger effects they noted in the 2000-06 period (around 1.1% as per Becker et al. (2010)) indicate that the reduced impact during 2007-13 is likely influenced by this tumultuous period.

With regards to previous periods, the estimate is slightly higher than some studies investigating previous periods, where Percoco (2017) of 0.8% found in 2000-06, Pellegrini et al. (2013) of 0.83% in 1994-2006 but lower than Becker et al. (2010) of 1.6% in the period of 1989-2006.

7.1.2 Parametric Estimates

Following the non-parametric analysis, the study proceeds with a parametric approach, as recommended by Jacob et al. (2012) and in alignment with Pellegrini et al. (2013). This approach serves as a further sensitivity check for the non-parametric estimates previously obtained and a baseline for the subsequent spatial analysis. Given the apparent absence of a treatment effect in the 2007-2013 period, the analysis presented will concentrate on the 2014-2020 period.

In Table 7.3 the parametric regressions is presented for various specifications according to Equation 5.3 in both level and logarithmic forms, and the model is selected based on the models that optimizes the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). [1] Model 3 emerges as the most efficient for both level and log, featuring a linear specification with interactions. This model's selection indicates that it offers the best trade-off between bias and variance, suggesting that the underlying functional form of the relationship is linear but allows for variations on either side of the threshold. This estimate is both insignificant and surprisingly small (0.08 in level and 0.24 in log).

Table 7.3: Parametric Estimates 2014-20 in Level and Logarithmic Form Over Different Specifications.

	In Level					In Log			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	1.846***	1.288**	0.0881	0.297	0.0201	0.468	0.235	0.0917	0.107
	(0.487)	(0.569)	(0.568)	(0.613)	(0.592)	(0.632)	(0.558)	(0.583)	(0.555)
Poly order	0	1	1⋆	2	2⋆	1	1⋆	2	2⋆
Observations	247	247	247	247	247	247	247	247	247
R^2	0.271	0.300	0.430	0.359	0.433	0.358	0.430	0.416	0.431
AIC	860.5	852.7	803.6	832.6	806.3	831.3	803.8	809.6	807.2
BIC	867.5	863.2	817.6	846.6	827.3	841.8	817.8	823.7	828.3
rmse	1.376	1.351	1.221	1.295	1.223	1.294	1.222	1.236	1.225

Note: Clustered standard errors at the country level in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

After specifying the functional form, following Jacob et al. (2012) the model incorporates covariates, and in this case also country-fixed effects as Becker et al. (2010, 2018). Additionally, the outermost observations on the left- and right hand side are dropped sequentially. By focusing the analysis on a more homogeneous set of data near the cutoff, which resembles the non-parametric approach using smaller bandwidths (Imbens and Lemieux, 2008). The inclusion of covariates and fixed effects helps address potential confounders and heterogeneity among the regions, thus refining the precision of the causal inferences drawn from the model.

Table 7.4 presents these results for Model 3 that was deemed the optimal specification in terms of AIC and BIC [2], across various configurations in both level and log transformations of the running variable. The model is examined in its simplest

[1] Higher-order polynomials where tested, but due to their lower performance in terms of both AIC and BIC is not presented here for space efficiency.

[2] AIC and BIC tests where performed on each restricted sample and Model 3 is the best performing model throughout in both level and log.

form without fixed effects or covariates, with the inclusion of fixed effects, and with both fixed effects and additional covariates, exploring how each configuration impacts the significance and magnitude of the treatment effect estimates. The trend of increasing significance and magnitude of estimates as the dataset is restricted to observations closer to the threshold indicates a more significant observable policy impact in these areas, consistent with the non-parametric estimates.

When country-fixed effects are added (Column 2 and 5), there is notable increase in the significance of the treatment effect estimates. This indicates that there is unobserved heterogeneity affecting treatment effect. The inclusion generally do not affect the estimates in any particular way compared to the fixed effects model. The trend is also consistent across both levels and log transformations of the running variable. The average value of the fully specified model is approximately 0.567% (level) and 0.529% (in log) average annual growth, which is quite similar to the 0.4% found by Crucitti et al. (2023) during the 2014-20 period. [3]

Table 7.4: Parametric Estimates 2014-20 in Level and Log Forms with Fixed Effects and Covariates: Restricted Samples

	Level			Log		
	(1)	(2)	(3)	(4)	(5)	(6)
Full Sample	0.0881	0.301	0.361*	0.235	0.122	0.184
	(0.568)	(0.232)	(0.194)	(0.558)	(0.223)	(0.185)
0.75	0.172	0.421	0.381	0.284	0.387	0.354
	(0.572)	(0.261)	(0.247)	(0.557)	(0.266)	(0.256)
0.65	0.260	0.490**	0.468**	0.338	0.461**	0.440**
	(0.600)	(0.198)	(0.189)	(0.588)	(0.199)	(0.192)
0.5	0.871	0.655***	0.664**	0.896	0.661***	0.672**
	(0.617)	(0.223)	(0.241)	(0.621)	(0.222)	(0.240)
0.4	1.058**	0.689***	0.741***	1.070**	0.687***	0.740***
	(0.468)	(0.152)	(0.174)	(0.469)	(0.151)	(0.176)
0.3	1.098*	0.758***	0.784***	1.115*	0.756***	0.781***
	(0.596)	(0.180)	(0.202)	(0.595)	(0.181)	(0.207)
FE	No	Yes	Yes	No	Yes	Yes
Covariates	No	No	Yes	No	No	Yes

Note: Clustered standard errors at the country level in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Covariates included are employment share in 2014 and population structure (median age) in 2014.

.

7.2 Validity of RDD

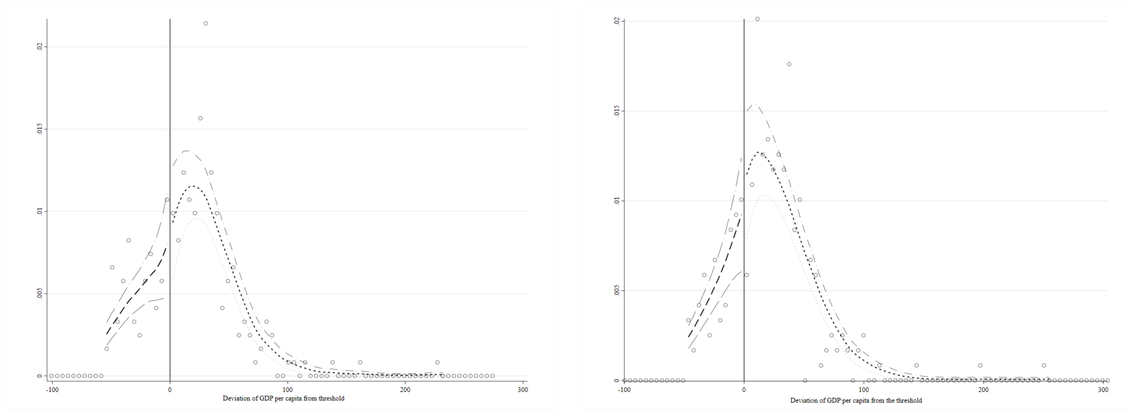
To ensure the robustness of the results various specification tests is employed in order to look for i) manipulation of the assignment variable , ii) possible jumps in

[3] Note that these results are not strictly comparable. Crucitti et al. (2023) found that the EU GDP was estimated to be 0.4% higher by the end of the policy implementation with respect to a hypothetical scenario without the policy.

the value of other covariates, iii) conducting "placebo" regressions to ensure that no significant effects emerge at other thresholds (Lee and Lemieux, 2010).

The continuity of the density of GDP per capita (the forcing variable) relative to the 75% threshold (the discontinuity point) is tested following the procedure of McCrary (2008). This is depicted graphically in Figure 7.2 for both programming periods. The figure shows a histogram and the estimated density of the data with standard error bands across the entire density curve to evaluate the robustness and reliability of the density estimates at and around the threshold.

A spike in density just below the 75% threshold would suggest manipulation by regions to qualify for objective status, where regions would try to fall below the threshold to receive treatment. The results for both periods do not show such a spike. Instead, there is a positive (insignificant) discontinuity estimate in both periods, indicated by a log difference in height, of 0.01 with a standard error of 0.32 for the first period and 0.13 with a standard error of 0.26 for the second period. These positive estimates, if anything, is rather suggestive of a higher density above the threshold, not below it which is clearly depicted in the graphs.



(a) Density 2007-2013 *(b) Density 2014-2020*

Figure 7.2: Density Check for Manipulation Around the Threshold.

A further test is to make sure that there is no discontinuities in variables that are determined prior to the assignment in order to check whether not only the treatment but also the covariates displayed a discontinuity at the threshold. (Lee and Lemieux, 2010). For this purpose, a number of candidate covariates that could in one way or another affect economic growth is graphically analyzed: employment share and the population structure (the median age of population) in Figures B.1. The graphs show no evidence of discontinuity. Neither does a robust non-parametric approach is employed to estimate the size of the discontinuity at the cutoff point for each selected covariate, all of which insignificant.

Lastly a placebo regressions is conducted to verify whether the significant effects observed at the original threshold are unique to the intervention. Thresholds both below and above, 65 and 90 GDP per capita is tested. The latter could be particularly important since this is the threshold for "Transitioning" regions in the 2014-20 period. However, neither show any significant results, see Table B.1.

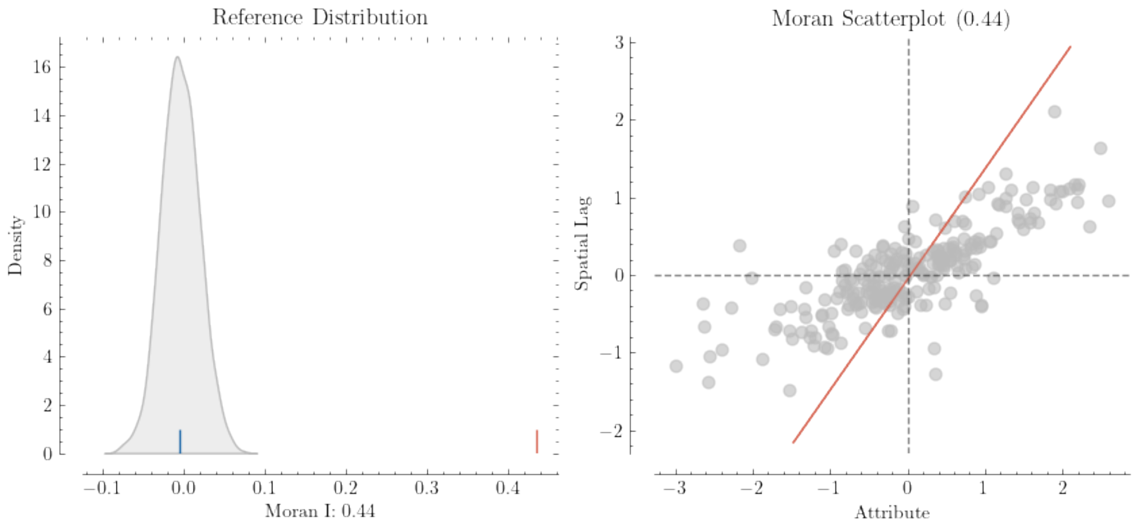
7.3 Considering Spatial Dependence

The last line of analysis is investigating spatial spillovers and to what extent does the EU cohesion policy in one region influence economic growth in neighboring regions. Accounting for the indirect cross-sectional dependence in the RDD framework is a novel approach developed recently by Cornwall and Sauley (2021), that developed a procedure using the Spatial Durbin Framework to allow for a full accounting of cross-sectional interactions. This method is crucial because, in the presence of cross-sectional dependence, parameters can become biased and inefficient (Anselin, 1988; LeSage and Fischer, 2008). Moreover, commonly used remedies such as spatial fixed effects and clustered standard errors, though previously employed in this study, may worsen these misspecification issues (Cornwall and Sauley, 2021).

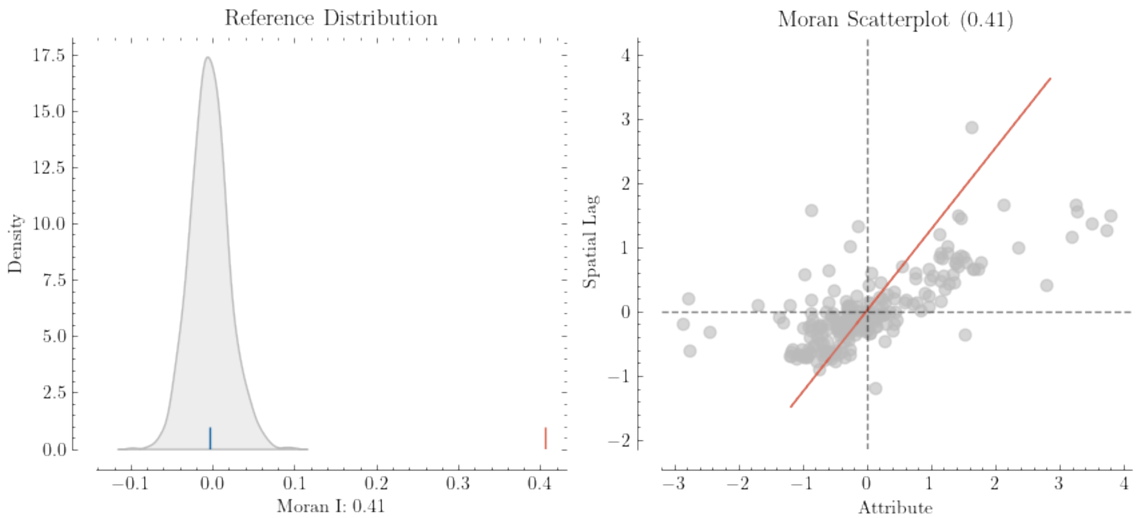
7.3.1 Spatial Diagnostic Tests

First, a Moran's I test is conducted on the preliminary OLS model. This measures the spatial autocorrelation by assessing the degree to which a variable at one location is similar to values of that variable at nearby locations, guiding whether spatial econometric models are warranted to begin with (LeSage and Fischer, 2008). The results suggest strong evidence against the null hypothesis of no spatial dependence with a value of 0.44 in 2007-13 and 0.41 in 2014-20 period. The Moran's I scatterplots, depicted in Figure 7.3 is a tool to visualize spatial autocorrelation, essentially showing whether similar values of a variable are located near each other across a geographic ares.

In the plot each dot represents a region, where the horizontal axis (Attribute) measures the GDP per capita growth, and the vertical axis (spatial lag) shows the average value of GDP growth for neighboring regions. A clear positive slope in the scatterplot, as observed here, indicates positive spatial autocorrelation. This means that regions with high values are typically surrounded by regions with similarly high values, and regions with low values are surrounded by areas with similarly low values. The histogram is the 'Reference Distribution' which illustrates the expected distribution of Moran's I values under the null hypothesis of no spatial autocorrelation. With no spatial patterns in the data, the Moran's I values would cluster around zero, but in this case the Moran's I (marked by the red vertical line) values stands out significantly to the right of this peak, indicating strong statistically significant spatial autocorrelation.



(a) 2007-2013



(b) 2014-2020

Figure 7.3: Morans Scatterplots in 2007-13 and 2014-20.

7.3.2 Spatial Regression Models

Next, the results from introducing the spatial regressions is presented in Table 7.5. The baseline OLS specification that was deemed the most suitable specification is presented in Table 7.3 compared to the Spatial Durbin Model (SDM), Spatial Lag Model (SLM) and Spatial Error Model (SEM) across two different matrices: Distance and Queen. The SLM incorporates both the lagged dependent variable (GDP per capita growth) and the lagged independent variable (Treatment), allowing for the assessment of both direct and indirect spatial effects. The SLM includes only the lagged dependent variable, while the SEM models spatial autocorrelation in the error terms (Anselin, 1988).

The SDM model reveal nuanced spatial interactions when comparing the two matrices: under the Distance matrix, the direct treatment coefficient changes sign to -0.26 (not significant), and the indirect effect (the spatial lag or treatment) is positive at 0.995, although not significant. Utilizing the Queen matrix, the direct treatment effect becomes even more negative, but still not significant. Here, the spatial lag of the treatment is positive and significant at 0.875. Furthermore, the spatial lag of the dependent variable (GDP per capita growth of neighboring regions, denoted Wy) is strongly statistically significant with a estimate between 0.440-0.904. While the indirect effect of the treatment is higher than the findings of Fidrmuc et al. (2024) that found an effect of approximately 0.3, the spatial lag of the dependent variable more similar (0.7).

When comparing the model specifications, the AIC and BIC are consistently lower for the spatial models compared to the baseline OLS, with the lowest values observed for models utilizing the Queen matrix. It is important to note that the spatial weight matrix and the Queen matrix has different economical interpretations: while the former defines the spatial relationships based on geographical proximity, the latter connects units sharing a border, and is thus more reflective of immediate and direct neighborhood effects, such as more local economic policies that might directly affect adjacent areas. While this still plausible economically, it comes with the price that islands aren't included, thus potentially skewing the analysis by omitting areas that, while geographically isolated, may still be economically significant.

However, the lowest value is for the Spatial Lag Model in both instances (Column 3 and 6). This suggest that the spatial autoccorelation is best captured by incorporating the spatial dependencies through the spatial lag of the independent variable.

Table 7.5: Results of Spatial Models using Distance and Queen Matrices 2014-2020

		Distance			**Queen**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Treatment	0.0850	-0.260	-0.124	0.0577	-0.482	0.0431	-0.105
	(0.298)	(0.307)	(0.279)	(0.302)	(0.322)	(0.271)	(0.335)
Indirect Treatment		0.995			0.875**		
		(0.958)			(0.403)		
Wy		0.873***	0.904***		0.866***	0.440***	
		(0.120)	(0.0903)		(0.121)	(0.0699)	
Model	OLS	SDM	SLM	SEM	SDM	SLM	SEM
Observations	241	241	241	241	241	241	241
AIC	783.1	763.1	762.2	774.5	759.5	752.6	753.1
BIC	797.0	787.5	783.1	795.4	783.9	773.5	774.0

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 7.6 the results from the 2007-2013 period is presented. The OLS model that is used as baseline specification is with a cubic polynomial and it interaction which was deemed as the most appropriate specification. [4] There is some quite confounding results to unpack. When including the indirect treatment, a strong negative significant coefficient is apparent when using a distance matrix. At the same time, the direct effect of the treatment becomes stronger and weakly significant. The interpretation of this suggests that the influence of the influence of the treatment on neighboring regions is negative - that while treatment might have beneficial effected within the treated region, it adversely affects nearby regions. Using a Queen matrix however, no such effect is seen.

The spatial lag of the dependent variable is particularly strong through all the models, even more so than in the 2014-2020 period. However, the SEM in column (4) is the specification with both lowest AIC and BIC. Here, the direct treatment coefficient becomes significant with a coefficient of 0.936. The SEM models spatial autocorrelation in the residuals, which means that the original OLS might be underestimating the treatment effect due to spatially correlated errors that OLS fails to address.

Table 7.6: Results of Spatial Models using Distance and Queen Matrices 2007-2013

		Distance			**Queen**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Treatment	0.312	0.809*	0.328	0.936**	0.325	0.266	0.357
	(0.597)	(0.435)	(0.459)	(0.428)	(0.455)	(0.464)	(0.476)
Indirect Treatment		-5.541***			0.0453		
		(0.850)			(0.430)		
Wy		3.790***	3.495***		3.074***	0.720***	
		(0.118)	(0.0624)		(0.151)	(0.0609)	
Model	OLS	SDM	SLM	SEM	SDM	SLM	SEM
Observations	239	239	239	239	239	239	239
AIC	871.0	731.6	767.0	730.0	762.2	783.7	798.6
BIC	898.9	769.8	801.8	764.8	800.5	818.5	833.3

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

After the spatial model, Cornwall and Sauley (2021) propose a strategy of "rezidualizing" the results from the spatial models and calculate the optimal bandwidth. In Table 7.7 this is presented for both periods. The results from the best performing model in (4) and (6) is the ones of interest for the respective periods, but the others are included for completeness. While the 2007-13 period does not show any significant results, the column (4) shows that the non-parametric results is similar to the ones obtained in Table 7.1 (see column (3) for 2014-2020), with similar coefficients but stronger significance with higher precision (lower standard errors). This could indicate that when purging the data from the spatial autocorrelation in the

[4] Although the parametric regressions for the 2007-2013 period were not detailed in the previous section, the model selection was based on achieving the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

data, when these "cleaned" residuals are used in further analysis, they provide a more accurate picture of the underlying relationship. This provides evidence that the results are robust when allowing the non-parametric methods to focus more directly on the variability and structure that might not be related to spatial effects. Furthermore, the large negative indirect treatment effect seen in the 2007-13 period is not apparent.

Table 7.7: Optimal Bandwidth from Spatial Models, 2007-13 and 2014-20.

	2014-2020				**2007-2013**			
	Distance		**Queen**		**Distance**		**Queen**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional	-0.981	-1.067	-1.016	-1.460***	0.122	-0.305	0.724	0.268
	(0.709)	(0.698)	(0.665)	(0.566)	(0.814)	(0.957)	(1.104)	(1.131)
Bias-corrected	-1.161	-1.248*	-1.209*	-1.663***	0.185	-0.452	0.606	0.150
	(0.709)	(0.698)	(0.665)	(0.566)	(0.814)	(0.957)	(1.104)	(1.131)
Robust	-1.161	-1.248	-1.209	-1.663**	0.185	-0.452	0.606	0.150
	(0.845)	(0.831)	(0.785)	(0.663)	(1.026)	(1.175)	(1.338)	(1.372)
Model	SDM	SLM	SDM	SLM	SDM	SEM	SDM	SEM

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Optimal bandwidth MSERD.

8

Conclusion

This thesis has critically evaluated the impact of the European Cohesion Policy on regional economic growth across the two latest programming periods from 2007 to 2020. By employing a quasi-experimental Regression Discontinuity Design (RDD) and integrating spatial econometric techniques, this study has provided insights into the causal effect of the policy, considering both its direct and indirect effects.

The first question addressed whether the policy has promoted growth in eligible, less developed regions. Along with most previous research assessing the impact of the policy, the results from this study indicate a positive but ambiguous impact on these regions economic growth. The findings indicate a differential impact across both regions and programming periods. Specifically, the 2014-20 period showed a positive effect, with an approximate 1-1.5% GDP per capita growth in regions below the 75% GDP per capita threshold. These results are primarily evident when estimates are made close to the threshold, as demonstrated by the non-parametric estimates that reveal significant effects only when the sample includes mainly those regions near the cutoff. This highlights a localized impact of the Cohesion Policy, fostering growth specifically in subgroup of regions that barely qualify for treatment. However, this poses limitations on the external validity for regions far away from the threshold, where the policy's effect are more challenging to discern. This may be because regions farther from the threshold do not rely as heavily on the policy due to the 'natural' convergence that occurs independently of the Cohesion Policy. The localized treatment effect is robust considering country fixed effects, but resulted in lower estimates between 0.4-0.8 %, indicating that the impact varies significantly depending on the regional characteristics and baseline economic outcomes.

Conversely, the results for the 2007-2013 period did not show significant policy impacts, likely indicative of the varying macroeconomic conditions during this time. This period was affected by significant economic turmoil and crises, following the 2008 financial crisis and the euro-zone crisis, which particularly impacted the Southern Europe countries.

The next question is related to the investigation of spillovers: to what extent does the policy in one region influence economic growth in neighboring regions, and does this enhance or undermine the policy's effectiveness? Significant spatial interactions was discovered in the data, but primarily related to the economic performance (GDP per capita growth) in nearby regions. No robust results where indicative of indirect treatment effects from policy interventions in these regions, meaning there is no indication that the policy has neither an undermining or enhancing effect on the policy. Although, when properly accounting for spatial effects related to neighboring regions economic growth obtained gave further support to the robustness of the RDD-estimates of about 1.5-1.7%.

Considering the range of average annual per capita growth rates from the most conservative estimate of 0.4% to the more optimistic 1.7%, there has been a total increase in per capita GDP ranging from 2.4% to 10.2% over the 2014-2020 period. With the per capita GDP of the treated regions being 59 percent of the EU-27 average and 112 percent for the non-treated regions (see Table 6.2), it would take between 38 and 161 years for the treated regions to converge to the economic levels of the non-treated regions based solely on the policy impact. Even considering the optimistic estimate, these results suggest that the policy has a modest contribution to reducing disparities between regions at different levels of development.

Although modest, these positive findings still have implications for future Cohesion Policy frameworks. The positive results for the 2014-20 period could suggest that EU's modified, more place-based approach - tailoring the funds to the unique characteristics of the recipient regions - has been more successful than the more narrow focus on convergence in 2007-13. However, to fully assesses whether this approach has successfully navigated the efficiency-equity trade-off inherent in regional policies, where the pursuit of equitable growth may come at cost of overall efficiency, further research is necessary. Furthermore, although positive results are found in the 2014-20 period, the lack of overall success during the 2007-13 period, particularly during crises, raises concerns about the policy's effectiveness under such conditions. Lastly, one of the main limitations of the study is that the link through which the policy affects growth is not explained. The policy has many different policy instruments, but the study only considers the average impact of the policy.

Furthermore, it is important to acknowledge that the policy pursues multiple goals beyond just economic growth, including the fostering of political stability and integration within the EU. This role is critical in mitigating social discontent and preventing political fragmentation, particularly in light of the rising support for Eurosceptic parties, a trend exacerbated by regional disparities and notably influential in the Brexit referendum (Dijkstra et al., 2020). Thus, the Cohesion Policy could be essential for fostering solidarity among EU member states and may be crucial for the EU's continued unity. However, this argument has its limitations. If substantial EU resources are invested in regions without demonstrating clear, measurable impacts, skepticism may grow among net-contributing member states about the efficacy of such expenditures

Lastly, the effects of this policy are also likely diffuse and long-term, making them challenging to capture through conventional short-term economic indicators used in this paper. Nevertheless, the persistent economic struggles of some regions, particularly in Southern Europe, indicate that the EU must continue to refine its approach to measuring and understanding the impacts of such policies.

Bibliography

Abreu, M., De Groot, H. L. and Florax, R. J. (2004), 'Space and growth: a survey of empirical evidence and methods'.

Angrist, J. D. and Pischke, J.-S. (2009), *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

Anselin, L. (1988), *Spatial econometrics: methods and models*, Vol. 4, Springer Science & Business Media.

Anselin, L. and Bera, A. K. (1998), 'Spatial dependence in linear regression models with an introduction to spatial econometrics', *Statistics textbooks and monographs* **155**, 237–290.

Bachtler, J. and Gorzelak, G. (2007), 'Reforming eu cohesion policy: A reappraisal of the performance of the structural funds', *Policy studies* **28**(4), 309–326.

Barca, F. (2009), *Agenda for a reformed cohesion policy*, European Communities Brussels.

Barone, G., David, F. and De Blasio, G. (2016), 'Boulevard of broken dreams. the end of eu funding (1997: Abruzzi, italy)', *Regional Science and Urban Economics* **60**, 31–38.

Barro, R. J. and Sala-i Martin, X. (1992), 'Convergence', *Journal of political Economy* **100**(2), 223–251.

Becker, B. S. O., Egger, P. H. and Ehrlich, M. V. (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**, 29–77.

Becker, S. O., Egger, P. H. and von Ehrlich, M. (2010), 'Going nuts: The effect of eu structural funds on regional performance', *Journal of Public Economics* **94**, 578–590.

Becker, S. O., Egger, P. H. and Von Ehrlich, M. (2012), 'Too much of a good thing? on the growth effects of the eu's regional policy', *European Economic Review* **56**(4), 648–668.

Becker, S. O., Egger, P. H. and Von Ehrlich, M. (2018), 'Effects of eu regional policy: 1989-2013', *Regional Science and Urban Economics* **69**, 143–152.

Boldrin, M. and Canova, F. (2001), 'Europe's regions: income disparities and regional policies', *Economic policy* **32**, 207–253.

Breidenbach, P., Mitze, T. and Schmidt, C. M. (2019), 'Eu regional policy and the neighbour's curse: analyzing the income convergence effects of esif funding in the presence of spatial spillovers', *JCMS: Journal of Common Market Studies* **57**(2), 388–405.

Cerqua, A. and Pellegrini, G. (2018), 'Are we spending too much to grow? the case of structural funds', *Journal of Regional Science* **58**(3), 535–563.

Cornwall, G. and Sauley, B. (2021), 'Indirect effects and causal inference: Reconsidering regression discontinuity', *Journal of Spatial Econometrics* **2**(1), 8.

Crescenzi, R. and Giua, M. (2020), 'One or many cohesion policies of the european union? on the differential economic impacts of cohesion policy across member states', *Regional Studies* **54**(1), 10–20.

Crucitti, F., Lazarou, N.-J., Monfort, P. and Salotti, S. (2023), 'The impact of the 2014–2020 european structural funds on territorial cohesion', *Regional Studies* pp. 1–15.

Dall'Erba, S. and Fang, F. (2017), 'Meta-analysis of the impact of european union structural funds on regional growth', *Regional Studies* **51**(6), 822–832.

Dicharry, B., Nguyen-Van, P. and Pham, T. K. C. (2019), '"the winner takes it all" or a story of the optimal allocation of the european cohesion fund', *European Journal of Political Economy* **59**, 385–399.

Dijkstra, L., Poelman, H. and Rodríguez-Pose, A. (2020), 'The geography of eu discontent', *Regional Studies* **54**(6), 737–753.

EUR-lex (2006), 'Council decision of 15 may 2006'. Number L 243, Volume 44, Date: 6.9.2006.

EUR-lex (2021), 'Regulation (eu) 2021/1058 of the european parliament and of the council of 24 june 2021 on the european regional development fund and on the cohesion fund'. Number L 231, Volume 60, Date: 30.6.2021.

European Commission (2010), 'Fifth report on economic, social and territorial cohesion - investing in europe's future'.

European Commission (2014), ‘Sixth report on economic, social and territorial cohesion - investing in europe’s future’.

European Commission (2017), ‘Seventh report on economic, social and territorial cohesion’.

European Commission (2024), ‘European commission regional and urban policy ninth report on economic, social and territorial cohesion’.

European Union (2008), *EU cohesion policy 1988-2008: investing in Europe’s future*, Office for Official Publications of the European Communities.

Eurostat (n.d.), ‘Nomenclature of territorial units for statistics’. https://ec.europa.eu/eurostat/web/nuts/overview [Accessed: 2024-05-23].

Fidrmuc, J., Hulényi, M. and Zajkowska, O. (2024), ‘The long and winding road to find the impact of eu funds on regional growth: Iv and spatial analyses’, *Regional Studies* **58**, 583–600.

Fratesi, U. (2024), *Regional Policy: Theory and Practice.*, 1st edn, Routledge.

Gagliardi, L. and Percoco, M. (2017), ‘The impact of european cohesion policy in urban and rural regions’, *Regional Studies* **51**, 857–868.

Gibbons, S. and Overman, H. G. (2012), ‘Mostly pointless spatial econometrics?’, *Journal of regional Science* **52**(2), 172–191.

Giua, M. (2017), ‘Spatial discontinuity for the impact assessment of the eu regional policy: The case of italian objective 1 regions*’, *Journal of Regional Science* **57**, 109–131.

Imbens, G. W. and Lemieux, T. (2008), ‘Regression discontinuity designs: A guide to practice’, *Journal of econometrics* **142**(2), 615–635.

Imbens, G. W. and Rubin, D. B. (2015), *Causal inference in statistics, social, and biomedical sciences*, Cambridge university press.

Jacob, R., Zhu, P., Somers, M.-A. and Bloom, H. (2012), ‘A practical guide to regression discontinuity.’, *MDRC* .

Kopczewska, K., Kudła, J. and Walczyk, K. (2017), ‘Strategy of spatial panel estimation: Spatial spillovers between taxation and economic growth’, *Applied Spatial Analysis and Policy* **10**, 77–102.

Krugman, P. (1991), ‘Increasing returns and economic geography’, *Journal of political economy* **99**(3), 483–499.

Lee, D. S. and Lemieux, T. (2010), 'Regression discontinuity designs in economics', *Journal of economic literature* **48**(2), 281–355.

LeSage, J. P. and Fischer, M. M. (2008), 'Spatial growth regressions: model specification, estimation and interpretation', *Spatial Economic Analysis* **3**(3), 275–304.

McCrary, J. (2008), 'Manipulation of the running variable in the regression discontinuity design: A density test', *Journal of econometrics* **142**(2), 698–714.

Mohl, P. and Hagen, T. (2010), 'Do eu structural funds promote regional growth? new evidence from various panel data approaches', *Regional Science and Urban Economics* **40**(5), 353–365.

Neumark, D. and Simpson, H. (2015), Chapter 18 - place-based policies, *in* G. Duranton, J. V. Henderson and W. C. Strange, eds, 'Handbook of Regional and Urban Economics', Vol. 5 of *Handbook of Regional and Urban Economics*, Elsevier, pp. 1197–1287.

Pellegrini, G. (2016), Measuring the impact of structural and cohesion funds using the regression discontinuity design: Final technical report, work package 14c of the ex-post evaluation of the erdf and cf 2007-2013, Working Paper Work Package 14c, European Commission.

Pellegrini, G., Terribile, F., Tarola, O., Muccigrosso, T. and Busillo, F. (2013), 'Measuring the effects of european regional policy on economic growth: A regression discontinuity approach', *Papers in Regional Science* **92**(1), 217–234.

Percoco, M. (2017), 'Impact of european cohesion policy on regional growth: does local economic structure matter?', *Regional Studies* **51**(6), 833–843.

Pieńkowski, J. and Berkowitz, P. (2016), Econometric assessments of cohesion policy growth effects: how to make them more relevant for policymakers?, *in* 'EU cohesion policy', Routledge, pp. 55–68.

Richardson, H. W. (1973), *Regional growth theory*, Macmillan.

Sala-i Martin, X. X. (1996), 'Regional cohesion: evidence and theories of regional growth and convergence', *European economic review* **40**(6), 1325–1352.

Appendix A

A.1 Data Sources

The data on the outcome- and control variables used is obtained from both Cambridge Econometrics database ARDECO and Eurostat. The information on Objective status the relative GDP per capita index it was decided upon, and payments from the EU is from is from the DG-Regio database (European Commission).

Table A.1: Data Sources

Variable	**Source**	**NUTS-version**
Eligibility (Period 1)	DG Regio	2003
Eligibility (Period 2)	DG Regio	2006
GDPpc index (PPS) (Period 1)	DG Regio	2003
GDPpc index (PPS) (Period 2)	DG Regio	2006
EU payments (Period 1 & 2)	DG Regio	2010/13
GDP (PPS) (2007-20)	ARDECO	2016
Population (2007-20)	ARDECO	2016
Employment share (2007)	Eurostat	2021
Population Structure (2007)	Eurostat	2021
Correspondence Tables	Eurostat	2003, 2006, 2010, - 2013, 2016

Note: Eligibility in period 1 and 2 refers to the Objective status that the region has been assigned based on the GDPpc index the relevant years (EU-27/28 = 100).

A.2 Data Mapping

The NUTS-2 regions that has undergone elementary changes, such as a change of name and code, can easily mapped by using the correspondence tables sequentially. Regions that experienced splits are adjusted to be represented with their previous classification and aggregated accordingly. The regions have been harmonized to the NUTS-2006 classification which is the version the eligibility for 2014-20 programming period was denoted in. This is because it minimizes the amount of regions that where not possible to map. Regions that has experienced more complex changes such as boundary shifts do not have a precise successor. These regions are mapped based on whether they share the same name, and where the regions structure has mostly survived. However, a few regions where not possible to properly map due to changes affecting the structure to much. These amounts to 7 regions for the 2007-13 period (DK00, DE41, DEE1, DEE2, DEE3, FI13 and SI00) and IE01 and IE02 in both.

Table A.2: Regions with Complex Changes in NUTS Versions

Type	Predecessor	Successor
2003-06		
Boundary shift	BG11	BG31
	BG12	BG32
	BG13	BG33
	BG23	BG34
	BG22	BG42
	BG23	BG34
	UKM1	UKM5
	UKM4	UKM6
2006-10		
Splits	FI18	FI1B, FI1C
Boundary shift	DED1	DED4
	DED3	DED5
	ITD5	ITH5
	ITE3	ITI3
	UKD2	UKD6
	UKD5	UKD7
2010-13		
Split	UKI1	UKI3, UKI4
	UKI2	UKI5, UKI6, UKI7
Boundary shift	FR91	FRA1
	SI01	SI03
	SI02	SI04
2013-16		
Split	LT00	LT01, LT02
	HU10	HU11, HU12
	PL12	PL91, PL92
	UKM3	UKM8, UKM9
2016-20		
Split	HR04	HR05, HR06, HR02

Note: Mayotte (FRA5) a new region in NUTS-2013 not included.

Between 2007 and 2013, the excluded regions, primarily from Southern Europe, received substantial funding despite not meeting typical objective criteria, as they were in countries with a Gross National Income (GNI) per capita below 90% of the

EU average. This included regions like Budapest and Bratislava. Notably, some Phasing-Out regions also received significant support, were mainly found in Spain with some in Germany and Austria. Ireland, heavily impacted by the financial crisis during this period, received a significant amount of funding the European Economic Recovery Plan due to it's (European Commission, 2010). In the second period (2014-2020), the focus shifted slightly with 6 regions changing their category and a continued high concentration of excluded regions in Southern Europe, totaling 18 out of 24.

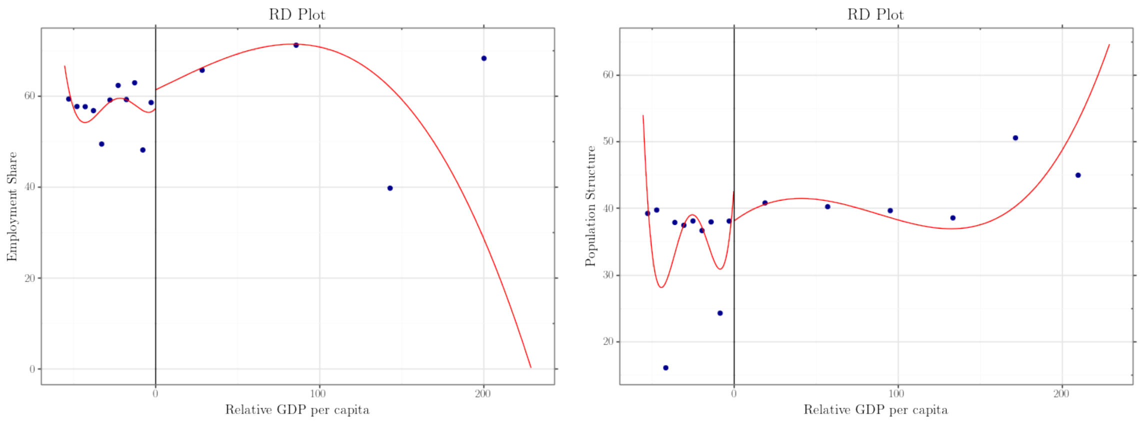
Table A.3: Non-Eligible Regions Receiving More EU-funds than Treated Regions in both Programming Periods.

NUTS ID	Name	Catg 07	Catg 14	Group	Switch
		2007-2013			
AT11	Lower Austria	PO	Transition	North-Western	No
DE42	Oberfranken	PO	Transition	North-Western	No
DED3	Dresden	PO	More developed	North-Western	No
ES12	Catalonia	PO	More developed	Southern	No
ES62	Andalusia	PO	Transition	Southern	No
FR83	Corsica	RCE	Transition	North-Western	No
HU10	Budapest	PI	More developed	Eastern	No
ITF5	Calabria	PO	Less developed	Southern	No
SK01	Bratislava	RCE	More developed	Eastern	No
		2014-2020			
DE80	Lower Saxony	Conv	Transition	North-Western	Yes
DEE0	Eastern Thuringia	NaN	Transition	North-Western	Yes
DEG0	Göttingen	Conv	Transition	North-Western	Yes
ES11	Balearic Islands	Conv	More developed	Southern	Yes
ES42	Canary Islands	Conv	Transition	Southern	Yes
ES61	Community of Madrid	Conv	Transition	Southern	Yes
GR13	Western Macedonia	PO	Transition	Southern	No
GR22	Epirus	Conv	Transition	Southern	Yes
GR25	Thessaly	Conv	Transition	Southern	No
GR30	Athens	PO	More developed	Southern	No
GR41	Ionian Islands	Conv	Transition	Southern	Yes
GR43	Aegean Islands	Conv	Transition	Southern	Yes
ITG2	Sicily	PI	Transition	Southern	No
MT00	Malta	Conv	Transition	Southern	Yes
PT15	Northern Portugal	PO	Transition	Southern	No
SI02	Slovenia	NaN	More developed	Eastern	No
		Both Periods			
ES63	Valencia	PO	More developed	Southern	No
ES64	Murcia	PO	Transition	Southern	No
ES70	Madrid	PI	Transition	Southern	No
GR24	Central Macedonia	PI	Transition	Southern	No
GR42	Crete	PI	More developed	Southern	No
IE01	Dublin	PI	More developed	North-Western	No
IE02	Cork	RCE	More developed	North-Western	No
PT30	Lisbon	PI	More developed	Southern	No

Note: This table categorizes regions by the period they were included in EU funding frameworks. 'Switch' indicates if there was a change from treatment in the first period the second. Eastern Thuringia, Slovenia (one region) are missing from the first programming period and Dublin and Cork are missing from both due to the mapping procedure.

Appendix B

B.1 Balancing Covariates



(a) Employment Share *(b) Population Structure*

Figure B.1: Continuity of Covariates. Note: the figure shows averages in evenly spaced bins of relative GDP per capita, using a 4th-order polynomial function.

B.2 Placebo Regressions

Table B.1: Placebo Regressions: 65 and 90 GDP per captia threshold.

	90 GDP per capita			65 GDP per capita		
	(1)	(2)	(3)	(1)	(2)	(3)
Conventional	0.486	0.444	0.235	-0.244	-0.290	-0.0594
	(0.553)	(0.551)	(0.596)	(0.839)	(0.776)	(0.765)
Bias-corrected	0.391	0.331	0.203	-0.0967	-0.217	0.0786
	(0.553)	(0.551)	(0.596)	(0.839)	(0.776)	(0.765)
Robust	0.391	0.331	0.203	-0.0967	-0.217	0.0786
	(0.635)	(0.632)	(0.694)	(0.999)	(0.885)	(0.848)

Note: Clustered Standard errors at the country level in parentheses, $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Optimal bandwidth is used MSERD.