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A helping hand, but not a lift. EU Cohesion Policy and regional development

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A Helping Hand, but not a Lift. EU Cohesion Policy and Regional Development*

Abstract

This study provides new evidence on the impact of the EU Cohesion Policy on income growth in less developed regions. Our panel includes data from all European regions for the years 1989-2020. Using a fuzzy Regression Discontinuity Design, we model treatment dynamics by applying a random effects estimator. Based on digitized historical data, we precisely replicate the policy rule and correctly classify the regions' eligibility status. Results show that the policy has a moderate positive effect on GDP per capita growth in the targeted regions.

Keywords: causal analysis, EU Cohesion Policy, regression discontinuity design, place-based policy

JEL classification: H20, R11, R58, Z18

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1 Introduction

Place-based policies are a central instrument for addressing regional inequalities worldwide. At the level of the European Union (EU), the Cohesion Policy has been the main policy scheme for promoting economic, territorial and social cohesion, particularly in less developed regions. It is one of the largest place-based policies in the world. However, spatial disparities in income across European regions are profound and persistent. In 2019, the gross domestic product (GDP) per capita of the richest region in Europe, the Grand Duchy of Luxembourg, was nearly nine times higher than that of the two poorest regions, Mayotte (a French overseas department) and the North-West region of Bulgaria.[1] Furthermore, the global financial crisis halted convergence in terms of regional GDP per capita within the EU. Moreover, regional disparities in income are growing in many EU countries.

Would regional disparities be greater if the EU and its member states did not implement the EU Cohesion Policy? Our study aims to answer this question, by analyzing the effect of funding in the context of Europe's largest place-based policy program. We contribute to the empirical literature by creating a novel dataset that allows treatment effect estimations on GDP per capita growth in less developed regions over five consecutive funding periods. Using historical data sources allows us to improve previous research on the proper classification of regions' compliance status and the use of a random effects model that considers variations in treatment not only over time, but also between regions in the estimates.

Previous studies examining whether the policy achieves its primary goal – fostering faster GDP per capita growth in less developed regions – found positive effects on income growth. The first causal evaluation of EU Cohesion Policy was conducted by Becker et al. (2010), who applied a Regression Discontinuity Design (RDD) to leverage the discontinuity in the intensity of fiscal transfers regions introduced by the 75 % eligibility threshold. Their analysis, which examined the first three funding periods (1989–2006), found positive income growth effects in less developed regions. By adding another funding period, Becker et al. (2018) largely confirmed the earlier findings. Similarly, Pellegrini et al. (2013) applied the same identification strategy to pooled data from the second and third funding periods (1994-2006); identifying positive effects on GDP per capita growth.

We follow the seminal paper by Becker et al. (2010) and apply a Regression Discontinuity Design. However, unlike previous studies on the EU Cohesion Policy, we determine a region's eligibility score using a novel dataset comprising information available at the time the EU Commission defined the list of regions eligible for convergence funding. Except for Lang et al. (2022), who examined policy-induced inequalities *within* regions, previous studies have relied on revised GDP per capita data to determine a region's position relative to the EU

1. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20210303-1.

average. However, such revised GDP per capita estimates fail to accurately capture regions' compliance with policy regulations. For instance, certain NUTS regions have been classified as 'never takers' (regions that are eligible but remain untreated). To the best of our knowledge, we are the first to show that accurately replicating the policy rule to determine eligibility for funding is crucial, as regression results are sensitive to how compliance status is defined, particularly near the cutoff.

Furthermore, using a richer dataset spanning 30 years, we offer a more comprehensive assessment of funding effects than previous studies that relied on shorter time frames and more limited data. Specifically, our panel data spans all five completed funding periods, allowing for a thorough examination of the treatment dynamics in this setting. Our findings indicate that most regions remain eligible for treatment across multiple consecutive funding periods. In fact, the relatively small number of switchers, defined as regions that change treatment status across funding periods, suggests that repeated treatment is the norm rather than the exception. This finding has significant implications for choosing an appropriate estimation approach.

Our findings indicate that the EU's place-based policy contributed to faster GDP per capita growth in less developed regions, increasing by 0.3 percentage points annually. While economically significant, this estimate for the policy-induced growth effect is lower than Becker et al. (2010, 2018); but closer to Pellegrini et al. (2013). Our results align with the limited number of regions that can exit funding during the observation period.

While our study focuses on identifying the average treatment effect, recent research highlights remarkable heterogeneity in the EU Cohesion Policy's efficacy in inducing growth across European regions (Di Caro et al. 2022; von Ehrlich 2024). Primary country-specific studies have examined the role of various contributing factors. While EU fiscal transfer intensity has only a negligible impact (Di Caro et al. 2022; von Ehrlich 2024), factors such as the type of funded projects (Cristofoletti et al. 2024; Di Cataldo et al. 2020) and regional characteristics, including human capital and the quality of institutions (Becker et al. 2013; Rodríguez-Pose et al. 2015; von Ehrlich 2024), urbanization and proximity to urban agglomerates (Gagliardi et al. 2017) or the size of the service sector (Percoco 2017) have been shown as key drivers of such heterogeneity.

The remainder of this study is presented as follows. Section 2 describes the EU Cohesion Policy in detail. Section 3 introduced the novel data used in our analysis. Section 4 presents descriptive evidence, and Section 5 outlined our estimation strategy. Section 6 discusses our results, while Section 7 presents comprehensive robustness checks. Section 8 summarizes the main results and concludes the study.

2 The EU Cohesion Policy

Over the years, the EU Cohesion Policy has become the EU's largest investment policy. During the last funding period (2014–2020), the EU allocated approximately one third of its budget (325 billion euros) to economic, social and territorial cohesion.[2] The policy scheme supports "job creation, business competitiveness, economic growth, sustainable development, and improve citizens' quality of life".[3] Expenditures mainly come from two Structural Funds: the European Regional Development Fund (ERDF) and the European Social Fund (ESF). The ERDF co-finances infrastructure projects in transportation, ICT, environment, and social sectors (e.g. hospitals, schools and housing). The ESF directly supports EU residents by co-financing programs that promote labor market participation and social inclusion.[4]

The EU Cohesion Policy represents the EU's place-based policy. Following Neumark et al. (2015, p. 1198), we define place-based policies as "government efforts to enhance the economic performance of an area within its jurisdiction, typically in the form of more job opportunities and higher wages". While the EU Cohesion Policy aims to enhance economic activity in already well-performing areas, it's primarily focus is on addressing spatial income inequalities by targeting less developed regions. Specifically, it's primary objective is to promote GDP per capita growth in less developed regions, defined at the NUTS-2 level having a GDP per capita $\leq$ 75 % of the EU average.[5] Only those regions are eligible for convergence funding (formerly called "Objective-1 funding"). During the 2014–2020 funding period, regions just above the 75% threshold received a maximum of 40% of the funding allocated to less developed regions.

After the European Commission determines eligibility (around one year before the start of a new funding period), a region typically keeps its status for the entire duration of the funding period, which can be five to seven years. Subsequently, eligibility is determined based on more recent data. Since it's introduction in 1989, the EU Cohesion Policy has been implemented

2. https://www.consilium.europa.eu/en/policies/eu-long-term-budget/long-term-eu-budget-2014-2020/

3. https://ec.europa.eu/regional_policy/en/policy/what/investment-policy/

4. Because of the broad nature of the EU Cohesion Policy, it influences not only GDP per capita. The effects on other economic and non-economic factors are the subject of recent empirical studies. Evidence points to mixed effects on employment (Becker et al. 2010; Giua 2017), positive effects on innovation activities (Ferrara et al. 2017), but no measurable impacts on local productivity growth (Albanese et al. 2021). Recent evidence on regional well-being indicators is also mixed (Ferrara et al. 2022; Albanese et al. 2024). Finally, Accetturo et al. (2014) show that the EU Cohesion Policy is connected to a deterioration of trust and cooperation in less developed regions.

5. Eurostat, the statistical office of the European Union, introduced a hierarchical classification system of regional units in EU member states. NUTS-2 regions generally reflect the administrative division of a country and have a population between 0.8 and 3 million. Examples of NUTS-2 regions are the *Bundesländer* in Austria, *regioni* in Italy, and *Comunidades y ciudades Autonomas* in Spain. In Germany, NUTS-2 regions correspond to *Regierungsbezirke* (German Länder are NUTS-1 regions). NUTS classifications are revised at irregular intervals to reflect changes in a member state's territorial divisions.
Figure A.1 in Appendix A shows maps of the regions that benefit from convergence funding.

for five funding periods, the first from 1989 to 1994, the fifth from 2014 to 2020. Importantly, the eligibility criteria remained unchanged, with only the underlying GDP per capita data being updated.

EU transfers to less developed regions are substantial. Figure 1 shows the funding intensity for the last funding period (2014–2020), measured by per capita and it's relation to the initial GDP. While all European regions receive some fiscal transfers, the funding intensity is considerably higher in regions eligible for convergence funding (marked as hatched areas). All less developed regions receive a minimum of 457 euros per capita (left panel, Figure 1), or at least 2 % of their initial GDP (right panel, Figure 1). Thus, all regions eligible for convergence funding fall into the highest funding category for both per capita funding and funding as a share of the initial GDP.

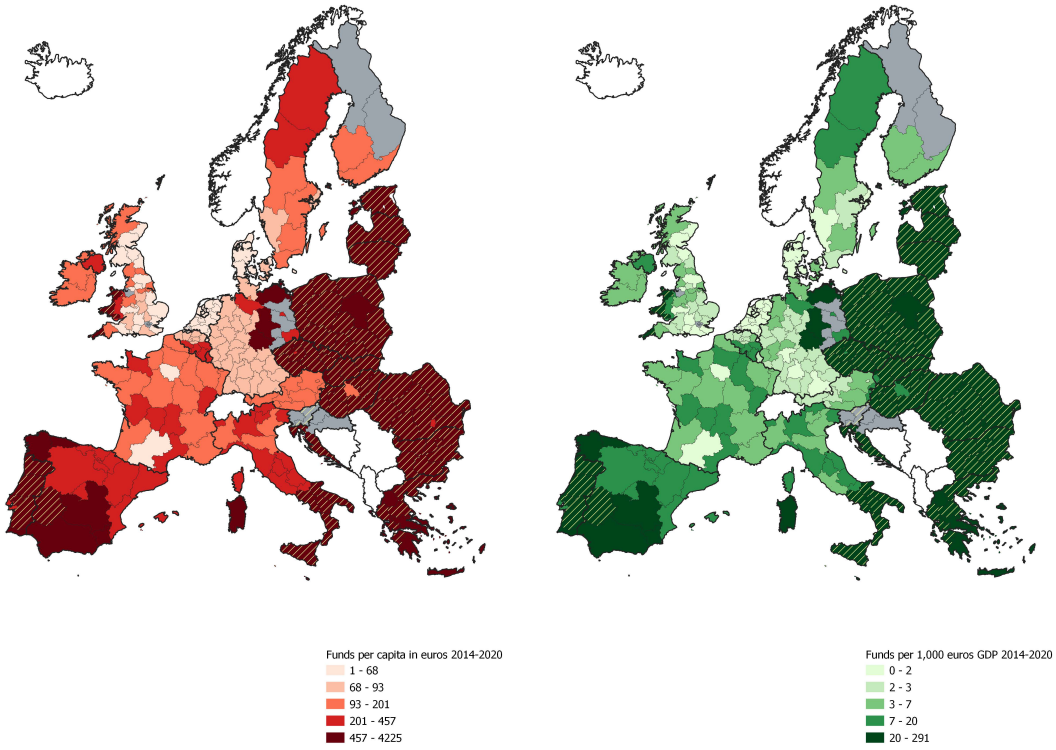

Figure 1: **Total funding per capita (left panel) and per initial GDP (right panel) during the 2014–2020 funding period**

Notes: EU payments to each NUTS2 region during the 2014–2020 funding period are divided by that region's population (left panel) or GDP (right panel) in the year preceding the funding period. Region boundaries follow the NUTS 2006 classification. Convergence-funded regions are marked as hatched areas.

Sources: European Commission's data on regionalized annual EU budget payments made by program period; own illustration.

3 Data, Sample and Variable Definitions

Our analysis of the EU Cohesion Policy's growth effects relies on a novel dataset, using historical data on regional GDP per capita at the NUTS2 level from the Eurostat publications. This data, used by the European Commission to determine eligibility for convergence funding, is available as scanned hard copies of Eurostat publications or press releases published about 1.5 years before the beginning of a new funding period. This dataset allows for a more precise replication of the policy rule compared to previous EU Cohesion Policy studies.[6]

Our dataset is an unbalanced panel at the NUTS2 regional level, comprising all five funding periods and all EU member states. A region might not be observed across all five funding periods for three different reasons.[7] *First*, the region (country) joined the European Union after the first funding period and was observed only upon gaining EU membership. *Second*, GDP per capita data were unavailable for some regions during certain periods. *Third*, regional harmonization to account for territorial reforms at the NUTS-2 level is not always possible. In our dataset, regional boundaries for a certain funding period correspond to the regional classification valid at the time eligibility was determined.[8] For transcoding, we use self-developed transition matrices.[9]

Based on the described data, our sample includes NUTS2-level data of all EU countries (except Croatia) in all five funding periods, excluding regions with an initial GDP per capita exceeding 175 % of the EU average.[10] Table 1 summarizes the number of included NUTS2 regions per funding period.

Outcome variable In our study, we examine the effect of EU Cohesion funding on regional GDP per capita growth. The outcome variable is defined as the average annual growth rate of the regional GDP per capita within a funding period.[11] If a region joins the EU during an ongoing funding period, its growth rate is calculated based on its years of EU

6. In Section 6, we show that the regression results are sensitive to the underlying database.

7. For more details, please refer to Appendix D.

8. Early regulations did not always specify the NUTS classification. In such cases, we determined the regional boundaries with the help of regional aid maps from the EU.

9. Our self-developed transition matrices track boundary changes in European regions from 1989 to 2020. They allow us to "back-code" recent regional data, typically classified according to the 2016 or 2021 NUTS definitions, to older NUTS classifications used at the time of eligibility decisions. We do not rely on population shares or weights for regional harmonization purposes. Instead, our matrices exploit the fact that many regional changes involve minor boundary shifts (which we ignore) or simple merges and splits, which can easily be reconstructed when recent regional data are available at the NUTS-3 level.

10. See Appendix D for a list of the excluded outliers, and Figure D.3 for a graphical presentation of the initial GDP per capita of the included regions.
In Section 7, we present the results of alternative estimations based on the full sample and for different bandwidths.

11. Although it would be interesting to analyze further outcomes, such as employment development or innovation activities, reliable data for this long observation period are not available for additional analyses.

Table 1: **Sample composition**

Funding period	**1989–1993**	**1994-1999**	**2000-2006**	**2007-2013**	**2014-2020**
	EU12	EU12	EU25	EU25	EU27
Recipients	35	47	101	83	69
Non-recipients	93	117	141	162	192
Total	128	164	242	245	261

Note: EU27 includes the UK but not Croatia.
Sources: EU legislation (see Table C.2 in Appendix C); own calculations.

membership. GDP per capita data (at constant 2015 prices) is sourced from the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO). Following OECD (2006) recommendations, we do not adjust regional GDP per capita for price-level differences across countries. However, inflation adjustment is necessary to avoid the impact of varying inflation rates across regions (countries) on our results.

Eligibility for funding Across all five funding periods, EU regulations stipulate the same eligibility rule: a NUTS2 region is eligible for convergence funding if its GDP per capita (in purchasing power standards [PPS]), based on data for the last three available years, is below 75 % of the EU average for the same reference period. However, the initial legislative texts on the Structural Funds do not specify which years were considered the last three available years or which countries were included in the Community average calculation. Table 2 presents the findings of our extensive research on this topic. Specifically, missing eligibility criterion details were supplemented with insights from the Directorate General of the European Commission in charge of the EU Cohesion Policy (DG Regio) and reports from various European institutions on program implementation.[12]

Table 2: **Policy rule by funding period**

	1989-1993		**1994-1999**	**2000-2006**		**2007-2013**	**2014-2020**
	EU12	GDR	EU15	EU15	A10	EU28	EU28
Ref. years	1983-85	-	1988-90	1994-96	1997-99	2000-02	2007-09
Ref. group	EU12		EU12	EU15	EU15	EU25(15)	EU27

Note: The German Democratic Republic joined the European Union in 1990 through German reunification. A10 refers to countries that became EU member states in 2004 (Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia).
Sources: EU legislation (see Table C.2, Appendix C) and DG Regio.

12. For more information on the data preparation and the accuracy of our data refer to Appendix D.

Eligibility status and funding Eligibility and funding status do not always align for all observed regions. In the early funding periods, the European Commission applied the eligibility rule flexibly when compiling the list of treated regions.[13] Convergence funding was granted to regions with missing GDP per capita data and that were clearly below the threshold. However, exceptions were occasionally granted to certain regions with a GDP per capita above 75 % of the EU average (based on the available data at the time).

Besides the above-mentioned funding exceptions in the earlier funding periods, we observe additional special features in the funding rules. During both the 2000–2006 and 2007–2013 funding periods, a transitional funding scheme called 'phasing-out funding' was introduced. However, we argue that the nature of phasing-out funding differed between the two periods.

In the 2000–2006 funding period, phasing-out funding was intended for regions that had benefited from convergence funding until the end of the 1994–1999 funding period but exceeded the eligibility threshold in the subsequent funding period. Therefore, we consider phasing-out regions in the 2000–2006 funding period as *not eligible but treated*, or *always-taker*.

In contrast, in the 2007–2013 funding period, phasing-out funding was used to protect regions from the 'statistical effect' caused by the drop in the average EU GDP per capita after the Eastern enlargement. Specifically, the EU introduced a second rule, according to which regions with a GDP per capita above 75 % of the EU-25 average but below 75 % of the EU-15 average qualified for phasing-out funding. We classify these regions as *eligible and treated*, or *compliers*.

The discrimination arises because phasing-out funding in the 2000–2006 period was an exception from the rule – those regions actually improved in terms of GDP per capita. In contrast, phasing-out funding in the 2007–2013 period was granted to regions that only relatively improved (due to the new composition of the group), but not in absolute terms.[14]

For our estimations, we define eligibility status and funding or treatment status as dummy variables. Figure 2 shows the eligibility and treatment status of all NUTS2 regions near the 75 % of the average GDP per capita threshold in the EU. We pool data from all five funding periods and present average treatment rates for equally sized bins of 1 percentage point. The figure shows that for all less developed NUTS2 regions (below the threshold), the treatment status corresponds to eligibility. The same applies to most of the "richer" regions (above the threshold), though exceptions are reflected. Overall, we observe a distinct jump in the treatment status at the threshold.[15]

13. Appendix C lists the relevant EU regulations.
14. In Section 7, we present estimation results using different classifications of phasing-out regions.
15. Figure B.2 in Appendix B shows that there is also a jump in funding intensity around the threshold.

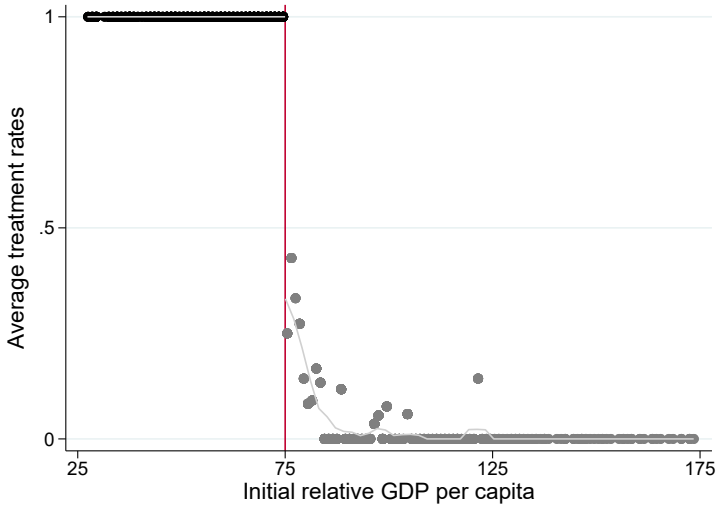

Figure 2: **Eligibility and funding status**

Notes: The figure shows the average treatment rates of the NUTS2 regions in the sample over the observed funding periods. The dots represent the average rates of all regions in equally sized bins of 1 percentage point. The fitted lines represent local polynomial smoothing of the treatment rates based on a rectangular kernel with rule-of-thumb bandwidth. The data for all five funding periods were pooled. Sources: Funding status: EU legislation (see Table C.2, Appendix C); score: Eurostat publications; own illustrations and calculations.

Additional data For robustness checks, we additionally use regional data on labor market conditions, capital and demographics from ARDECO and Eurostat.[16] Specifically, to capture labor market conditions, we compute the employment rate, employment share in agriculture and manufacturing, employee compensation and household net disposable income. We also calculate population density and net migration to account for regional-level demographics. Finally, we include capital stock and gross fixed capital formation.

4 Descriptive Statistics

4.1 Compliance to the funding rules in our data

The exceptions to the policy rule for funding share a common feature: we observe only non-eligible treated regions (*always-takers*) but no eligible non-treated regions (*never-takers*) (see

16. For more details, see Appendix C.

Figure 2). Table 3 provides a more detailed description of the regional compliance status in our sample across the five observed funding periods.

This classification of compliance status represents a key contribution to the empirical literature on the economic effects of the EU Cohesion Policy. Previous studies have mainly used revised GDP per capita data to determine eligibility for convergence funding. We argue that revised GDP per capita data fail to accurately capture regional compliance status, as the regional GDP per capita is estimated using *current (i.e. subsequently corrected)* information for a past year. This may lead to erroneous classification of certain regions as *never-takers*.

Table 3: **Compliance status**

	Non-recipients	Recipients
1989–1993		
Non eligible	93	5
Eligible	0	30
Total	**93**	**35**
1994–1999		
Non eligible	117	6
Eligible	0	41
Total	**117**	**47**
2000–2006		
Non eligible	141	12
Eligible	0	89
Total	**141**	**101**
2007-2013		
Non eligible	162	0
Eligible	0	83
Total	**162**	**83**
2014-2020		
Non eligible	192	0
Eligible	0	69
Total	**192**	**69**

Sources: Own calculations.

Becker et al. (2013, p. 39) explain that:

> the regional GDP figures that national statistical agencies report to Eurostat may be inaccurate (or even not available at all) at the time eligibility for funding is determined and might later be revised by Eurostat with no effect on foregone funding. In our data, which are revised GDP figures available from Cambridge Econometrics, some regions are below the 75 percent threshold ex post, but they were not at the time the EU Commission had to decide on eligibility.

Our historical data confirm this assumption. This reflects that regions classified as *never-takers* in other studies were actually ineligible ex-ante and thus did not receive convergence funding. By not taking the treatment, the regions were compliant with the rule applicable to the data available at the time of the eligibility decision. In summary, the advantage of our study is that the use of historical data for the forcing variable allows us to capture the true compliance behavior and accurately estimate the effects of the EU Cohesion Policy. The

results in Section 6 show that misclassifications can significantly influence or bias estimated funding effects.

4.2 Persistence of the treatment status

Table 4 shows the 'treatment dynamics' of the regions in our sample, with each column representing a cumulative time horizon (e.g. 1989–1999 includes the first two funding periods). For each horizon, we classify regions into 'Always treated', 'Never treated' and 'Switchers' —- the last one representing those that changed treatment status over time. For example, by the end of 1999, 44 regions received convergence funding in both periods, 117 received none and three became beneficiaries only in the second period only (see column (2)).

As Table 4 shows, the treatment status remains largely stable across funding periods with only a few regions changing their treatment status over time and even fewer exiting the convergence funding regime entirely. Moreover, column (5) of Table 4 shows that not all observed exits from convergence funding reflect absolute improvements in regional income levels. Some changes in treatment status are driven by relative shifts in EU-wide GDP distribution. For the 2014 funding period, the 75 % cutoff was based on the average GDP per capita of all EU-27 countries, including the poorer member states from the 2004 and 2007 Eastern enlargements. Column (5) shows that had the policy rule continued to be lenient, 25 additional regions[17] would have been eligible for convergence funding, 14 of which had already received support during the 2007 funding period and would have continued to do so.[18]

These patterns highlight two important points for interpreting policy-induced effects and identification: The low number of switchers, especially the low number of regions exiting convergence funding, sets an upper bound on the potential magnitude of policy-induced growth effects. The EU Cohesion Policy aims to foster income growth in less developed regions. If the policy were highly effective, many regions would cross the eligibility threshold over time and thus no longer qualify for convergence funding. Of course, one would argue that strong but temporary effects could lead to frequent switching in and out around the eligibility cut-off. However, even this pattern appears to be rare. Although limited, some regions do exit

17. The number of 25 additional regions is the difference between the total number of treated regions under the standard cutoff (column (4)) and under the counterfactual EU15-based cutoff (column (5)). The treated regions included those that were always treated, switched in, switched out and in, or switched thrice. The total number of treated regions increased from 69 to 94 treated regions, a difference of 25.

18. Out of the remaining 11 regions, six regions would have received funding for the first time (among which 1 region simply because it is observed for the first time in period 5 due to boundary changes), and five regions would have switched back into convergence funding (after previously moving (in and) out).

Table 4: **Treatment status dynamics**

Funding period	(1) **1989-1999**	(2) **1989-2006**	(3) **1989-2013**	(4) **1989-2020**	(5) **1989-2020 (EU15*)**
Always treated	44	97	81	69	82
Never treated	117	140	142	148	142
Switcher					
Switching In	3	4	2	0	7
Switching Out	0	1	17	39	23
Switching In and out	-	0	3	5	2
Switching Out and in	-	0	0	0	4
Switching thrice	-	-	0	0	1
Total	164	242	245	261	261
Reference group	EU12	EU15	EU15	EU27	EU15*

Sources: own calculations.

convergence funding over time, and only a few regions enter treatment or oscillate around the eligibility cutoff. This suggests moderate policy-induced income gains.[19,20]

The moderate within-region variation in treatment status, especially in the early funding periods, also raises key identification considerations. In our sample, 44 regions switched status over the observed five funding periods (see column (4)). By the end of the third funding period only five regions changed their treatment status (see column (2)). This poses a challenge for studies relying primarily on within region variation over time. In contrast, our study uses both time variation (changes in treatment status within regions) and cross-sectional variation (differences across regions) to estimate treatment effects. Moreover, Table 4 presents only actual treatment status, without considering eligibility. Our historical data reveal that, of the 44 regions that eventually switched out of treatment status, 12 were non-compliant with the policy rule at least once as they benefited from convergence funding despite being ineligible. This further reduced the pool of relevant switchers for estimating of the average treatment effect of compliers. In Section 6, we compare the results of both panel models within

19. The treatment dynamics shown in Table 4 reflect the actual treatment status by funding period, but decisions on convergence funding are based on GDP per capita from the most recent available years prior to the funding decision, which may already be several years old by the time funding is implemented. For example, the first funding period (1989–1993) was based on 1983–1985 data, and the second period (1994–1999) used 1988–1990 data. As a result, even if convergence funding had immediate effects on regional growth, these would not appear in the treatment classification shown in Table 4 until funding period three (column 2).

20. Eligibility for convergence funding is based on GDP per capita measured in current prices and adjusted for purchasing power standards (PPS), while we measure regional growth in terms of real GDP per capita in constant prices and without PPS adjustment. While these are not identical, sustained real GDP growth should influence a region's eligibility status over time.

our estimation framework and data and show that incorporating cross-sectional differences enhances estimation precision.

4.3 Development of regional GDP per capita

To obtain a first impression of possible policy-induced convergence dynamics, we compare the evolution of less developed regions (that receive convergence funding) with non-funded regions. Figure 3 plots the average annual GDP per capita growth rate of both funded and non-funded regions in the sample over the past 30 years. Regional annual growth rates above 100 % indicate positive growth, while values below 100 % signify a decline in regional annual GDP per capita.

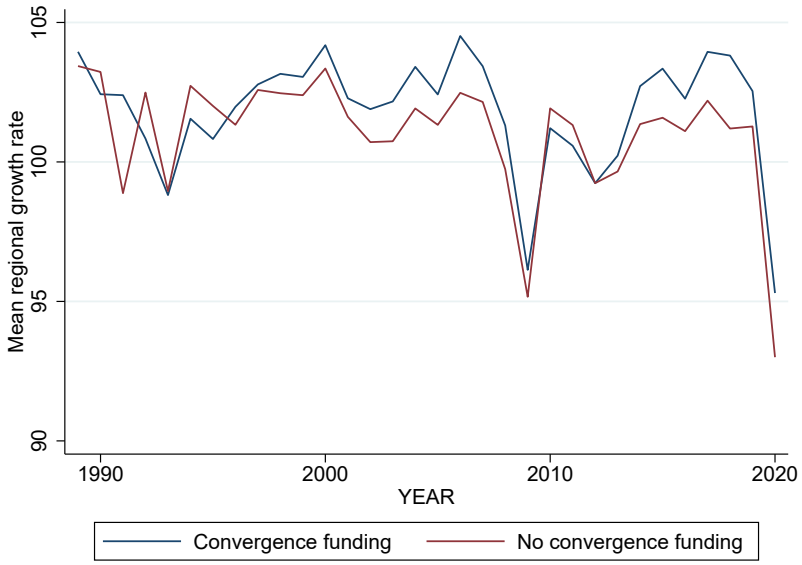

Figure 3: **Evolution of GDP per capita growth rates over time**

Notes: The figure shows the average annual GDP per capita growth rates for the funded and non-funded NUTS2 regions in the sample. GDP per capita is measured at 2015 prices.
Sources: Outcome: ARDECO; funding status: EU legislation (see Table C.2, Appendix C); own illustrations and calculations.

During the covered period, funded regions exhibited higher income growth rates than non-funded regions. However, the figure suggests only minor differences between these two groups. The difference in the mean annual growth rates is approximately 0.74 percentage points and rarely exceeds 2 percentage points. In summary, less developed regions experience faster growth, though at a modest pace.

In the next step, we switch from the time-series perspective to a cross-sectional comparison of regions based on their initial income levels. We graphically examine income growth rates of the NUTS2 regions in the sample near the eligibility threshold for convergence funding. Figure 4 presents the study results, showing the regional average annual growth rate over a funding period, pooled for the five observed funding periods. Figure 4 confirms that less developed regions exhibit faster growth. However, the strongest growth is observed in the very poorest regions, while the discontinuity in the average annual growth rates around the 75 % threshold remains minimal.

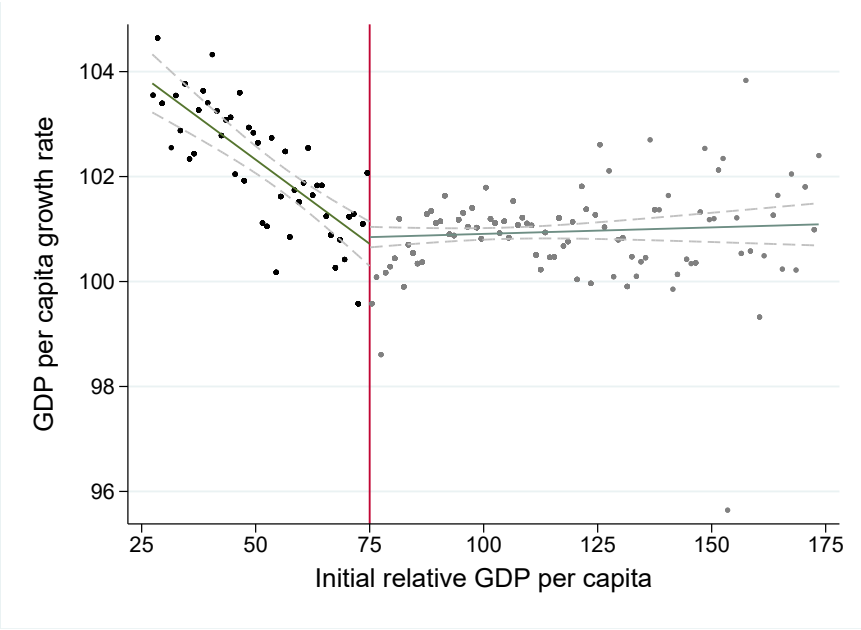

Figure 4: **GDP per capita growth rates around the threshold**

Notes: The figure shows the average annual GDP per capita growth rates of the NUTS2 regions in the sample over the funding period. The dots represent average rates of all regions in equal sized bins of 1 percentage point. The fitted lines represent local polynomial smoothing of the growth rates based on a rectangular kernel with a rule-of-thumb bandwidth. Data for all five funding periods are pooled. Always-takers were excluded.
Sources: Outcome: ARDECO; score: Eurostat; own illustrations and calculations.

5 Empirical Strategy

To estimate the causal effect of the EU Cohesion Policy on regional growth, we apply a Regression Discontinuity Design (RDD) – a quasi-experimental research designs that uses an exogenously determined discontinuity in treatment assignment for policy evaluation. This

section presents the chosen model specification and then verifies whether the conditions for applying an RDD are fulfilled.

5.1 Model specification

We use a fuzzy RDD and data from 1989 to 2020 to estimate the effect of the EU Cohesion Policy on regional GDP per capita growth. Because some regions received convergence funding despite having a relative GDP per capita above the 75 % threshold (see Table 3), we apply a two-stage least squares specification (Imbens et al. 2008; Gelman et al. 2019):

$$D_{it} = \gamma_0 + \gamma_1 \, E_{it} + \gamma_2 \left(X_{it}\right) + \zeta_t + \gamma_{3,t} \left(X_{it}\right) \times \zeta_t + \xi_{c(i)} + \mu_i + \nu_{it} \tag{1}$$

$$Y_{it} = \beta_0 + \beta_1 \, D_{it} + \beta_2 \left(X_{it}\right) + \eta_t + \beta_{3,t} \left(X_{it}\right) \times \eta_t + \theta_{c(i)} + \rho_i + \epsilon_{it} \tag{2}$$

where Y_{it} denotes the per-capita GDP growth of region i in the funding period t. The coefficient of interest, β_1, captures the discontinuity in regional GDP per capita growth at the cutoff, that is the treatment effect. D_{it} denotes the treatment status and takes the value 1 if NUTS-2 region i receives convergence funding in period t. The forcing variable, X_{it}, is defined as the region's initial GDP per capita relative to the EU average, measured in PPS and calculated from the information available at the time of the EU Commission's eligibility decision. As we use five funding periods for the estimation, we normalize the absolute values of the respective cutoffs (i.e. the value corresponding to 75 % of the EU average GDP per capita in the respective funding period) to 0.75 and relate the regional GDP per capita values to this normalized cutoff. Following (Imbens et al. 2008), we allow for different slopes of the forcing variable on either side of the cutoff. Figure E.4 in Appendix E confirms the smoothness of the forcing variable around the cutoff. We interact the forcing variable with the period dummy η_t (ζ_t in the first stage) to capture period-specific differences in the functional relation between forcing and outcome variable.[21] Moreover, we allow for country-specific intercepts by including country dummies, $\xi_{c(i)}$ and $\theta_{c(i)}$, respectively, while μ_i and ρ_i account for unobserved heterogeneity.

Unlike previous literature that used region fixed effects (e.g. Becker et al. (2010)), we apply a random effects estimator. We argue against including region fixed effects as only a few regions switch in or out of convergence funding, especially in the earlier funding periods (see Table 4). The identification of the treatment effect would rely solely on the few regions with variations in treatment status over time. Instead, applying random effects allows us to

21. A graphical inspection of the functional form $f\left(X_{it}\right)$ (see Figure F.8 in Appendix F) exhibits different slopes in the five observed funding periods, confirming the necessity of considering period-specific functional relations.

exploit the panel structure of our data, using regional variation in treatment status both over time (within regions) and in the cross-section (between regions) for the estimation.

Implicitly, this random effects IV model assumes that the treatment effect β_1 is constant across funding periods. We verify this assumption of homogeneous treatment effects over time in detail in Section 7. The model also assumes there are no carry-over effects into the next funding period. This assumption is supported by the results of previous studies suggesting that once a region loses eligibility, the effects of the EU Cohesion Policy vanish quickly (Becker et al. 2018; Barone et al. 2016; Di Cataldo 2017).

We use a parametric Panel IV regression due to an insufficient number of observations near the cutoff for non-parametric estimations (see Becker et al. (2010) for a similar decision). The standard errors are clustered at the regional level to account for serial correlation.

5.2 Validity of the RD design

To ensure the validity of an RDD, a significant jump in the treatment assignment at the cutoff value of the forcing variable is required. In Section 3, we describe the eligibility and treatment status of all NUTS2 regions near the cutoff. Figure 2 exhibits a clear change in the treatment assignment at the cutoff.[22] Furthermore, the slope of the forcing variable must be smooth at the cutoff. Figure E.4 (Appendix E) shows that this assumption is also fulfilled.

A further crucial assumption is that the assignment to treatment is exogenous to the regions. Lee et al. (2010) argue that in an RDD, the assumption of exogeneity is fulfilled at least in the vicinity of the cutoff value if the actors have limited control over the forcing variable. Following previous literature, we argue that regions did not have precise control over their eligibility for funding (Becker et al. 2013). To influence the forcing variable, regions could implement policies that, for instance, improve well-being without fully exploiting the region's GDP per capita growth potential. However, despite political economy considerations, a region cannot target a specific level of GDP per capita. Alternatively, regions would have to falsify data, which is also very unlikely, as regional GDP per capita data are compiled at the national level, and countries have less incentive to falsify data than regions. Moreover, both forms of manipulation require an accurate prediction of the 75 % cutoff value in advance. However, this cutoff is defined in relation to the EU average per capita income over a three-year time interval, and regional GDP per capita data is measured in PPS to adjust for price-level differences across EU countries. In addition, we perform a density continuity test (presented in)Figure 5), that shows no evidence of manipulation as the density function of the forcing variable is smooth around the cutoff. If regions had manipulated the data, we would likely

22. In addition, the treatment intensity reveals a jump at the cutoff, as shown in Figure E.4 (Appendix E).

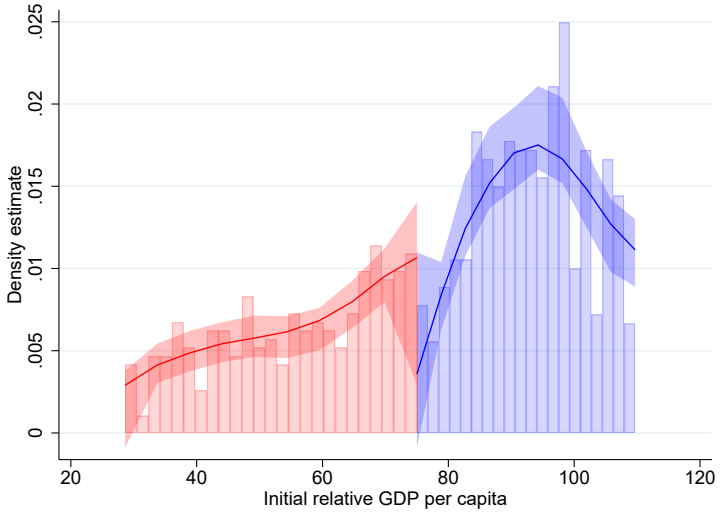

Figure 5: **Manipulation testing**

Notes: Testing manipulation using density estimation for the forcing variable. Data for all five funding periods are pooled.
Sources: Eurostat; illustration: Cattaneo et al. (2018)

observe a density jump left of the cutoff value with regions seeking to enter the funding (Cattaneo et al. 2018; McCrary 2008).[23]

Finally, covariates potentially influencing the outcome must be continuous around the cutoff to interpret the observed effect as the treatment's causal influence. We test whether observable regional characteristics representing demographics, capital resources and labor market conditions are continuous around the cutoff. Due to data availability constraints, we can only test the continuity assumption for funding periods from 2000 onwards. We specify the covariates analogous to the forcing variable, that is, computing a three-year average over the reference years indicated in Table 2. We graphically examine the covariates for discontinuities at the eligibility threshold (Figures E.6 and E.7 in Appendix E) and observe no significant jumps in the data.

6 Results

In this section, we present our results, including findings from our main model presented in Section 5 based on the historical dataset, on revised data, and estimations based on a fixed effects estimation.

23. See Appendix E for funding period-specific manipulation tests.

Table 5 provides evidence for the positive effect of convergence funding on the regional average annual growth rate of GDP per capita. The size of the coefficient in column (1) indicates a policy-induced annual growth effect of 0.3 percentage points for the period 1989 to 2020. This positive effect is consistent with the findings of previous studies. However, the estimated effect is remarkably lower than that reported by Becker et al. (2010), who estimated a 1.6 percentage point faster GDP per capita growth in less developed regions between 1989 and 2006. By extending the time span of their analysis by one funding period, Becker et al. (2018) mainly confirmed their previous results. In contrast, Pellegrini et al. (2013) find average annual GDP per capita growth effects of 0.6 percentage points when combining the 1994–1999 and the 2000–2006 funding periods. We argue that our results support the observation that over the past 30 years of EU Cohesion Policy, only a few regions were able to sustainably increase their GDP per capita relative to the EU average, and switch out of convergence funding. Nevertheless, the estimated effect still represents a significant economic impact of the EU Cohesion Policy.

The results also show the influence of period-specific functional relations between eligibility and GDP per capita growth. The significant coefficients of the interaction terms confirm that considering the period-specific relationships improve the model and allows for an accurate estimation of the funding effect.

We now focus on what distinguishes our study from previous studies: *first*, the use of historical data, and *second*, the choice of a random effects estimator. In the following, we verify how these differences influence the results.

As we described in Section 3, our approach differs from previous studies by using historical GDP per capita data, allowing us to replicate the eligibility decisions of the EU commission. To address potential sensitivity to the data used, we present the result of our estimation model 2 using revised GDP per capita data in column (2) of Table 5.[24] The estimated effect of EU Cohesion Policy is much smaller and statistically insignificant, highlighting the importance of accurately capturing the compliance behavior of economic actors in the estimations. Although previous studies classified only very few regions as 'never-takers', this misclassification can significantly bias estimation results, because these regions are close to the cutoff and thus receive the highest weights in the estimation.[25]

24. The difference in the number of observations in columns (1) and (2) of the table is the result of a somewhat different sample composition for each model. Regions for which historical data are not available drop out of our main sample used in column (1), but are included in the sample based on revised GDP per capita data for the forcing variable used in column (2).

25. For instance, Becker et al. (2013) classify 11 NUTS-2 regions as 'never-takers'. While this corresponds to only 1.7 % of their sample, nine of those regions are in the closest vicinity of the 75 % cutoff (between 70 % and 75 %).

Table 5: **Main results**

	(1) RE model, hist. data	(2) RE model, rev. data	(3) FE model, hist. data
Conv. funding	0.3368*	0.1319	0.3492
	(0.183)	(0.242)	(0.307)
$f_0(X_{it})$	0.0054	0.1015	-2.7071***
	(0.535)	(0.381)	(0.877)
Period2 × $f_0(X_{it})$	-0.8519	-0.7243	-1.2683**
	(0.706)	(0.520)	(0.621)
Period3 × $f_0(X_{it})$	-1.2266**	-0.7476	-0.8689
	(0.607)	(0.485)	(0.578)
Period4 × $f_0(X_{it})$	1.2728*	0.4202	1.2571*
	(0.686)	(0.526)	(0.741)
Period5 × $f_0(X_{it})$	-0.4324	-0.4639	-0.1275
	(0.698)	(0.493)	(0.754)
$f_1(X_{it})$	-2.2257	-8.1053***	-5.8512**
	(2.054)	(2.090)	(2.590)
Period2 × $f_1(X_{it})$	3.6957	7.4171***	8.5358***
	(2.333)	(1.825)	(2.225)
Period3 × $f_1(X_{it})$	3.0113	7.8214***	3.5158
	(2.382)	(2.460)	(2.407)
Period4 × $f_1(X_{it})$	2.7957	10.2043***	3.3367
	(2.267)	(2.436)	(2.517)
Period5 × $f_1(X_{it})$	5.2243*	10.6733***	1.9196
	(2.707)	(2.837)	(2.707)
Constant	101.6524***	101.4332***	101.7713***
	(0.215)	(0.147)	(0.246)
Period dummies	yes	yes	yes
Country dummies	yes	yes	no
Observations	1040	1130	1040

Notes: Robust standard errors in parentheses; significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The estimations presented in columns (1) and (3) are based on historical data, and those in column (2) on revised data. The estimated models in columns (1) and (2) show random effects estimations (see eqn. 2), in column (3) fixed effects are shown.
Sources: Eurostat, ARDECO; own calculations.

Another difference between our analysis and previous studies lies in the model specification. Becker et al. (2010) applied a fixed effects model using panel data. In contrast, while our analysis also relies on panel data, we estimate the treatment effect using a random effects estimator. To show the impact of the chosen model, we present the results of a fixed effects IV model based on our sample in column (3) of Table 5. The coefficient obtained is comparable in size to our specification in column (1), however, it remains insignificant. A potential explanation for the low precision is that the fixed effects model identification relies on variations within regions over time. However, only 44 out of 261 regions in our sample switch treatment status between funding periods (Table 4). The comparison confirms that, within the scope of this study, using a random effects estimator is preferable.

7 Robustness Tests

In this section, we first validate the assumption of homogeneous treatment effects, which is implicitly made in the above-mentioned estimation model. We then conduct comprehensive robustness tests, as the results may be particularly sensitive to alternative sample compositions and variable specifications, and alternative estimation models.

7.1 Verification of the effect homogeneity assumption

We apply the described model to estimate the effect of the EU Cohesion Policy across various combinations of at least three subsequent funding periods as a validity test. The assumption of homogeneous treatment effect is considered as fulfilled, if the estimated treatment effect is similar for different sub-periods of the observation period. Table 6 summarizes the results. Overall, the results across the considered combinations of funding periods confirm our main results, indicating that the assumption of homogeneous treatment effects is met.[26] The coefficient in column (1) is an exception, though, showing a positive, but small and statistically insignificant effect of the EU Cohesion Policy for the funding periods 1 to 3. This may suggest a less successful kick-off of the EU Cohesion Policy in 1989. Alternatively, the result may be influenced by the number of non-eligible regions benefiting from convergence funding in the first funding period, which are not included in our sample due to data availability issues. Thus, we might not fully capture the impact of the EU Cohesion Policy for the first funding period.

26. Applying an estimation model for time-dependent treatment effects would circumvent this assumption. However, despite a comprehensive debate on this topic in the current econometric literature, we do not find any random effects model for time-varying treatment effects in current econometric literature. Recent models in the literature (Sun et al. (2021), De Chaisemartin et al. (2020), and Wooldridge (2021)) are enhanced fixed effects models.

Table 6: **Homogeneous treatment assumption**

	(1) Period 1 to 3	(2) Period 1 to 4	(3) Period 2 to 4	(4) Period 2 to 5	(5) Period 3 to 5
Conv. funding	0.1441	0.4395*	0.4330*	0.3524*	0.4607**
	(0.263)	(0.242)	(0.244)	(0.186)	(0.198)
$f_0(X_{it})$	0.6401	0.0359	-0.9229	-0.9140	-1.4264***
	(0.482)	(0.547)	(0.635)	(0.626)	(0.425)
$f_1(X_{it})$	1.2471	-2.0270	1.8552	1.6849	1.1877
	(2.552)	(2.177)	(1.586)	(1.604)	(1.483)
Observations	534	779	651	912	748

Notes: Estimation of the effect of convergence funding on regional GDP per capita growth for different subsets of funding periods. Regressions use the forcing variable based on historical data. (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).
Sources: Eurostat, ARDECO; own calculations.

7.2 Robustness against alternative sample composition and variable specification

Definition of the outcome variable The definition of the period for GDP per capita growth concerned the EU Cohesion funding is not straightforward. Payments are made throughout the funding period after project approval. There may be a time lag between a new funding period and the first payment receipts. Moreover, the spending rule has changed over time, i.e., allowing payments for committed expenses for up to one year ('n+1 rule'), and up to three years after the end of a funding period ('n+3 rule'). Table 7 shows that estimations are robust to different definitions of the GDP per capita growth periods.[27] In particular, calculating GDP per capita growth using the 'n+1 rule' does not change our results, see row (1) of panel (1) in Table 7. Also when accounting for gradual relaxation of the spending rule over the various funding periods (row 2), and that certain countries start spending the money earlier than others[28] (row 3), the effect remains positive and statistically significant.

Classification of phasing-out regions The sample composition varies when different classification schemes are used for the phasing-out regions, which may also influence the estimation results. We test the robustness of our findings against two alternative classification schemes. First, we classify the phasing-out regions during the 2000 period as non-eligible non-treated ('complier') rather than non-eligible treated ('always-taker'). Second, we adjust the classification of the phasing-out regions in the 2007 funding period. Instead of classifying

27. The results in rows (1) to (3) of panel (1) are estimated excluding the 2014 funding period, as reliable GDP data at the regional level are available only until 2021, but in all EU countries, a substantial amount of funds was spent in the subsequent year(s).

28. Spending patterns by country are available here.

Table 7: **Robustness tests: sample and variable specifications**

	observations	coefficient	std.err.	$P > \|z\|$
initial model	1040	0.3368*	0.183	0.066
(1) alternative outcome variable specifications[1]				
'n+1 rule' time span	780	0.4412*	0.229	0.054
period-specific time span	779	0.3932*	0.235	0.094
country-period-specific time span	779	0.4233*	0.241	0.080
(2) alternative classification of phasing-out-regions				
Period 3	1040	0.3216*	0.174	0.064
Period 4	1040	0.5001***	0.183	0.006

Notes: All regression results represent estimations using the forcing variable based on historical data. (*** p < 0.01, ** p < 0.05, * p < 0.1)

[1] Results are estimated excluding the 2014 funding period for data availability reasons.

Sources: Eurostat, ARDECO; own calculations; own calculations.

regions as eligible treated, we categorize them as non-eligible non-treated (again 'complier', but on the other side of the cutoff). The findings in panel (2) of Table 7 show that our results are robust to different classification schemes.

7.3 Robustness against alternative model specifications

Functional relation of forcing variable and outcome Next, we examine the results of alternative specifications of the assignment function, starting with our preferred model of flexible first-order polynomials of the forcing variable including interactions with period dummies. we then modify the definition stepwise: *first*, we use second-order polynomials of the assignment function, *second*, we do not interact the assignment function with the period dummies, and *third*, we combine both modifications. Table 8 shows that our regression results are sensitive to the specified changes. Using time-fixed assignment functions and/or second-order polynomials results in a loss of precision for the treatment effect estimation (see rows (2) to (4) of panel (1), Table 8). While the effect remains comparable in size to our main result, it becomes insignificant. These findings highlight the importance of considering potential variations in the correlations between the treatment assignment and the GDP per capita growth across different funding periods.

Next, we assess the influence of exceptions granted by the EU Commission (see Section 3) to ineligible regions by estimating an OLS (sharp RD design). If regions securing policy exceptions were those likely to perform well even without the convergence funding, we would expect the OLS coefficient to be upwards biased. Conversely, if exceptions were granted only to regions with particularly sluggish economies, then we can expect the OLS coefficient to be

smaller than the IV estimate. The OLS regression result is presented in row (1) of panel (1) in Table 8. The OLS regression coefficient remains, but smaller than that of the IV approach (see Table 5), and is statistically insignificant. The results suggest that the IV approach is able to correct for this important bias. Moreover, it shows that convergence funding is typically granted to regions with characteristics negatively correlated with income growth, i.e. regions that severely suffered from industrial decline.

Bandwidth selection For our estimation, we use a sample consisting of a comparatively broad range of regions, i.e. we exclude only very rich regions (see Section 5). Panel (2) of Table 8 presents the results of alternative sample definitions applying different bandwidths of two, one and 1/2 standard deviations on either side of the cutoff and the results based on the full sample (including outliers). One standard deviation represents a ± 30 percentage point variation in initial GDP per capita around the EU average.

Restricting the sample to regions within two standard deviations leads to a policy-induced growth effect of 0.4 percentage points (row (1)), while for regions within one standard deviation the effect is 0.6 percentage points (row (2)). Estimating our model using the full sample also confirms our main result (see row (4) of panel (2)). Overall, our results remain across different bandwidth selections. However, narrowing the bandwidth to 1/2 standard deviations significantly reduces the number of observations to about one-third of the preferred sample, leading to an insignificant funding effect (row (3)).

Including control variables We test if regions on both sides of the cutoff are similar in terms of their demographics, capital resources and labor market conditions. To test for the influence of covariates on the treatment effect, we include the above-mentioned covariates in our estimation model. Panel (3) of Table 8 presents the results of the different specifications. The first row of panel (3) shows our estimation results for funding periods 3 to 5 in the absence of covariates. Rows (2) to (4) of panel (3) show estimation results including covariates representing labor market, demographics and capital resources, respectively.[29] The results show that the aforementioned covariates do not affect the treatment effect: the coefficient remains relatively stable in size and significance across all specifications. The only exception is an insignificant treatment effect when capital resources are included, likely due to the significantly smaller number of observations. Furthermore, we use different combinations of covariates in the estimation. Row (5) gives the estimation results including demographic and labor market variables, and row (6) of panel (3) includes all specified covariates. These results also confirm the robustness of our estimation against the inclusion of control variables.

29. *The labor market* variables are: employment rate, employment share in agriculture and manufacturing, compensation of employees and households' net disposable income. *Demographics* are considered by population density and net migration, while *capital resource* covariates are capital stock and gross fixed capital formation.

Table 8: **Robustness tests: model specifications**

	observations	coefficient	std.err.	$P > \|z\|$
initial model	1040	0.3368*	0.183	0.066
(1) alternative functional relation of forcing variable and outcome				
OLS	1040	0.1786	0.164	0.276
$p2^1$, period interactions	1040	0.3934	0.286	0.170
$p1^1$, no period interactions	1040	0.2731	0.184	0.137
$p2^1$, no period interactions	1040	0.2558	0.280	0.361
(2) alternative bandwidth selections				
2 standard deviations	987	0.3873**	0.192	0.044
1 standard deviation	679	0.6071**	0.247	0.014
1/2 standard deviation	325	0.4760	0.477	0.318
full sample	1054	0.3520*	0.180	0.051
(3) inclusion of control variables				
no covariates	748	0.4607**	0.198	0.020
incl. demographics	711	0.4209**	0.206	0.041
incl. labor market	711	0.3922*	0.210	0.062
incl. capital	619	0.3800	0.237	0.109
incl. demographics & labor market	711	0.4152*	0.214	0.052
incl. all covariates	619	0.4762*	0.240	0.047

Notes: All regression results represent estimations using the forcing variable based on historical data. Because of data availability, regression results in panel (3) are based on funding periods 3 to 5 and include covariates accounting for regions' demographics (population density, and net migration), capital resources (capital stock and gross fixed capital formation) and labor market conditions (employment rate, employment share in agriculture and manufacturing, compensation of employees, and households' net disposable income). (*** p < 0.01, ** p < 0.05, * p < 0.1)

[1] Polynomial of order 1 or 2 of the functional form, respectively.

Sources: Eurostat, ARDECO; own calculations.

8 Concluding Remarks

This study analyses the impact of the EU's place-based policy on fostering income growth in less developed regions. Our analysis uses a new dataset of historical regional GDP per capita figures at the NUTS-2 level, specifically the data used by the European Commission to determine eligibility for convergence funding. We show that using these historical GDP vintages is essential for accurately capturing regional compliance status and that it has important implications for identification in our empirical design.

Our results indicate that while the EU Cohesion Policy has a positive and economically significant effect on regional GDP per capita growth, its impact is moderate. This aligns with the observation that relatively few regions have transitioned out of eligibility over time. If the policy had substantial and sustained effects on regional GDP per capita growth, more regions would be expected to surpass the 75 % threshold of the EU average and lose access to convergence funding. Our findings are consistent with the empirical literature suggesting that the policy's growth effects are not necessarily long-lasting. Several studies indicate that once a region loses eligibility for convergence funding, the positive effects on GDP per capita growth tend to dissipate (Barone et al. 2016; Becker et al. 2018; Di Cataldo 2017).

From a methodological perspective, the sensitivity of our results to the treatment assignment replication has implications for policy evaluation studies using fuzzy RDDs. Our findings highlight the need for accurately capturing the policy rule as fuzzy RDDs rely on the implied eligibility status as an instrumental variable, especially in settings where identification relies on a limited number of observations near the cutoff.

Overall, our results highlight the challenges of fostering economic convergence within the European Union. Although place-based policies can provide a temporary boost to regional development, ensuring sustained long-term effects remains a major policy challenge. A growing body of research examines the conditions under which the EU Cohesion Policy is most effective across different regional contexts. An important avenue for future research is to not only identify where or when the policy is most effective, but also examine how it can generate persistent, and long-term economic benefits.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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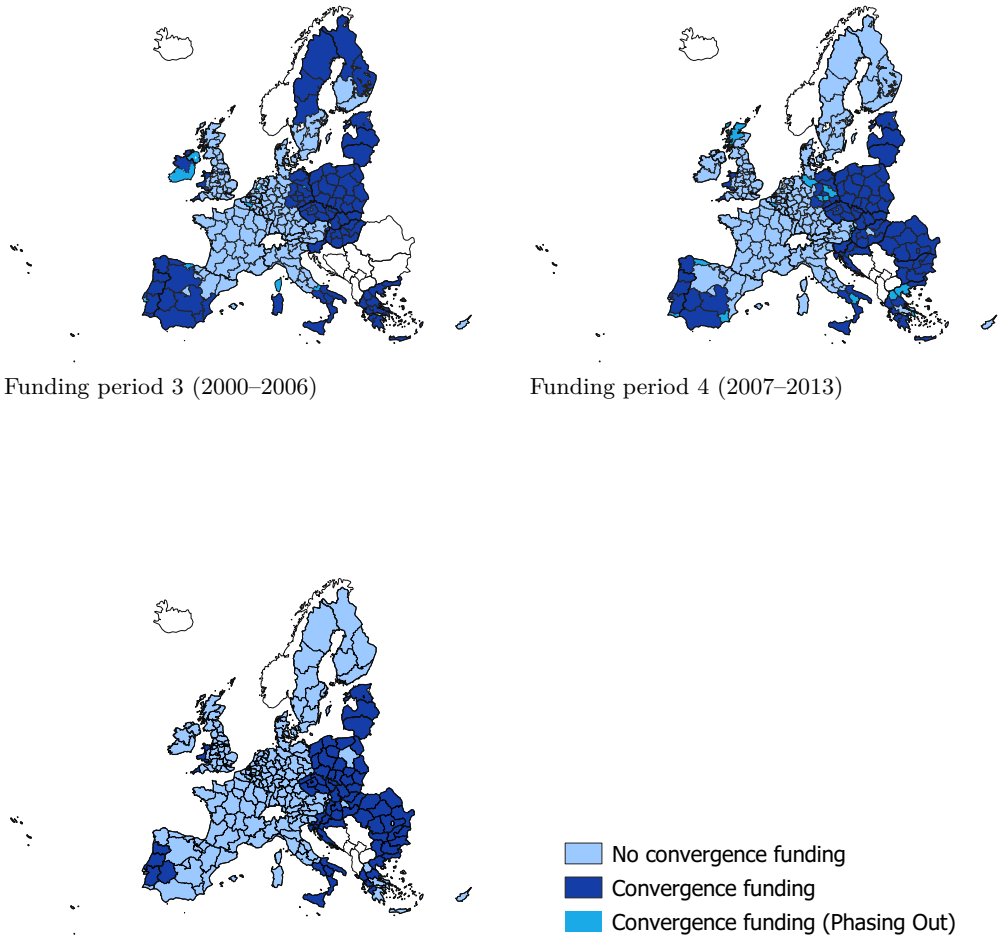
Appendix

A Convergence funding from 2000 to 2020

The maps in Figure A.1 show in dark blue the regions that benefited from convergence funding during the funding periods 3 to 5, respectively.[30] Phasing-out funding is represented in turquoise while the remaining regions are depicted in light blue.



Funding period 3 (2000–2006)

Funding period 4 (2007–2013)

Funding period 5 (2014–2020)

Figure A.1: **Convergence funding from 2000 to 2020**

Notes: The figures map the regions benefiting from convergence funding during the 2000–2006, 2007–2013 and 2014–2020 funding periods.
Sources: EU legislation (see Table C.2 of Appendix C); own calculations.

30. The respective geo-information for the maps (shapefiles) is not available for the historical NUTS2-classifications used in the 1989 and 1994 funding period.

B Discontinuity in funding intensity

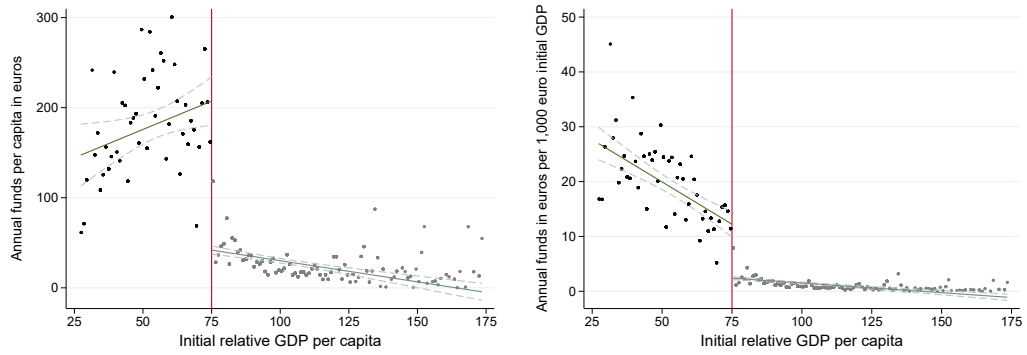


Figure B.2: **Discontinuity in funding intensity**

Notes: The figures show the funding intensity at the regional level in equally sized bins of 1 percentage point which are plotted against the forcing variable for regions with an initial relative GDP per capita up to 175 % of the EU average. Funding intensity is defined as average annual funds per capita over one funding period (left panel) or as average annual funds per initial GDP (right panel). Data for all five funding periods are pooled.
Sources: outcome: Historic EU payments, ARDECO; score: Eurostat.

C Data sources

Table C.1: **Data sources**

Variable	Year	Description	Source(s)
Income			
Revised GDP, constant prices	1983 - 2020	Revised GDP data in 2015 prices	ARDECO (04.03.2024)
Revised GDP, current prices	1983 - 2020	Revised GDP data in current prices, adjusted for purchasing power parity (PPS)	ARDECO (04.03.2024)
Labor market			
Unemployment rate	1994 - 2009	Unemployed persons over civilian labor force	ARDECO (04.03.2024)
Employment rate	1994 - 2009	Total employment over civilian labor force	ARDECO (04.03.2024)*
Empl. share in agriculture	1994 - 2009	Employment in agriculture over total employment	ARDECO (04.03.2024)*
Empl. share in manufacturing	1994 - 2009	Employment in manufacturing over total employment	ARDECO (04.03.2024)*
Compensation of employees	1994 - 2009	Compensation of Employees in Euros (2015 prices)	ARDECO (04.03.2024)
Households' net disp. income	2000 - 2009	Households net disposable income in Euros	ARDECO (04.03.2024)
Capital			
Capital stock	1994 - 2009	Capital stock in Euros	ARDECO (04.03.2024)
Gross fixed capital formation	1994 - 2009	Gross fixed capital formation in Euros (2015 prices)	ARDECO (04.03.2024)*
Demographics			
Population	1983 - 2020	Number of persons (Demographic Statistics)	ARDECO (04.03.2024)*
Population density	1983 - 2020	Number of persons per square kilometer	ARDECO (04.03.2024)*, Eurostat
Net migration	1990 - 2009	Net migration (number of persons)	ARDECO (04.03.2024)
Life expectancy	1994 - 2009	Life expectancy of newborn in years	Eurostat
Dependency ratio	1994 - 2009	Ratio of economically dependent population (persons aged below 15 or above 65) over economically productive population (persons aged between 15 and 65):	Eurostat
			*UK data from ARDECO (07.04.2021)

Table C.2: **Data sources for policy rule**

Policy rule	List of treated regions	Historical GDP per capita data
Funding period 1989–1993		
Council Regulation 2052/88	Council Regulation 2052/88, Annex	Basic Statistics of the Community. Editions 24, 25 and 26.
Funding period 1994–1999		
Council Regulation 2081/93	Council Regulation 2081/93, Annex I	Rapid Reports. Regions. Theme 2, published in 1990, 1991, 1993
Funding period 2000–2006		
Council Regulation 1260/99	Commission Decision (1999/502/EC)	Statistics in focus. General Statistics. Theme 1 - 1/1999 and 2/2002
Act of Accession 2003	Act of Accession 2003, Annex I	
Funding period 2007–2013		
Council Regulation 1083/2006	Commission Decision (2006/595/EC)	Eurostat press release STAT/05/47, published April 7, 2005
Funding period 2014–2020		
Regulation No 1303/2013 of the European Parliament and of the Council	Commission Decision (2014/99/EU)	Eurostat press release 38/2012, published March 13, 2012

D Sample composition

Table D.3 reports the number of European regions, recipient and non-recipient, for each funding period. For every country, we use the NUTS classification that (presumably) was applied when eligibility was determined by the European Commission.

Regions can be missing in our sample for one of three reasons: i) because the European Commission itself, when determining eligibility, lacked data at the required level of aggregation, ii) because despite our efforts we miss the data based on which the Commission determined eligibility, or iii) . Furthermore, we exclude regions with an initial GDP per capita above 175 % of the EU average, as they are outliers.

Undetermined eligibility We have to exclude regions for which eligibility could not be determined from our sample, since we want to replicate the Commission's decision. The new sample composition is reported in Table D.4.

The main reason for undetermined eligibility is the lack of regional GDP per capita data the list of regions eligible for convergence funding was set up. In such cases, convergence funding was assigned based on the belief whether a region's GDP per capita was above or below 75 % of the EU average. For the first funding period, this concerns all East German regions, Overseas France, the Portuguese autonomous region of Madeira and the Azores as well as the Dutch region Flevoland, which was newly established in 1986. For the second funding period, the European Commission still lacked data for East Germany, Madeira and the Azores. By way of exception, the European Commission included all territories within the scope of convergence funding, but Flevoland.

Table D.3: **Sample with full coverage**

Number of regions	Treatment status				
Funding period	**1989–1993**	**1994-1999**	**2000-2006**	**2007-2013**	**2014-2020**
	EU12	EU15	EU25	EU28	EU28
Recipients	51	61	97	86	71
Non-recipients	128	145	145	168	202
Phasing-out	-	-	10	16	-
Total	179	206	252	270	273
Classifications	*1992*	*1995*	*1999, 2003*	*2003, 2006*	*2006*
	1985, 1995	*1992*			

Sources: EU legislation (see Table C.2 of Appendix C); own calculations.

Table D.4: **Sample with known eligibility status**

Number of regions	Treatment status				
Funding period	**1989–1993**	**1994-1999**	**2000-2006**	**2007-2013**	**2014-2020**
	EU12	EU15	EU25	EU28	EU28
Recipients	36	50	97	86	71
Non-recipients	95	145	145	168	202
Transitional support	-	-	10	16	-
Total	131	195	252	270	273

Sources: EU legislation (see Table C.2 of Appendix C); own calculations.

Eligibility for British NUTS-2 regions could also not be determined as the United Kingdom provided Eurostat only with data at the more aggregated NUTS-1 level. Therefore, none of the 33 British regions could be considered for convergence funding by default, even if some would have been eligible.

Data availability We miss data on historical GDP per capita for the first funding period new Member States joined the EU, as well as Ireland in period 3. Table D.5 reports the sample of regions for which we have historical GDP per capita

Regional harmonization Finally, a few regions are missing from our sample due to changes in the territorial boundaries of NUTS-2 regions over time. To address this, we adjusted the data for our outcome variable — originally available only in the current NUTS classification — to align with the historical boundaries of the regions.

Outlier We exclude six regions with a GDP per capita above 175 % of the EU average, which we determined as outliers based on the distribution of initial relative GDP per capita

Table D.5: **Sample with historical GDP per capita data available**

Number of regions	Treatment status				
Funding period	**1989–1993**	**1994-1999**	**2000-2006**	**2007-2013**	**2014-2020**
	EU12	EU12	EU25	EU25	EU27
Recipients	36	49	96	70	69
Non-recipients	95	123	145	168	202
Transitional support	-	-	9	16	-
Total	131	172	250	254	271

Sources: EU legislation (see Table C.2 of Appendix C); own calculations.

shown in Figure D.3. Those regions are: the Dutch region *Groningen* (periods 1 and 5), the German region *Hamburg* (periods 1,2,3 and 5), the British region *Inner London* (periods 3-5), the Belgian capital region *Région de Bruxelles* (periods 4 and 5), the French capital region *Île de France* (period 5), and the state of Luxembourg (period 4 and 5).

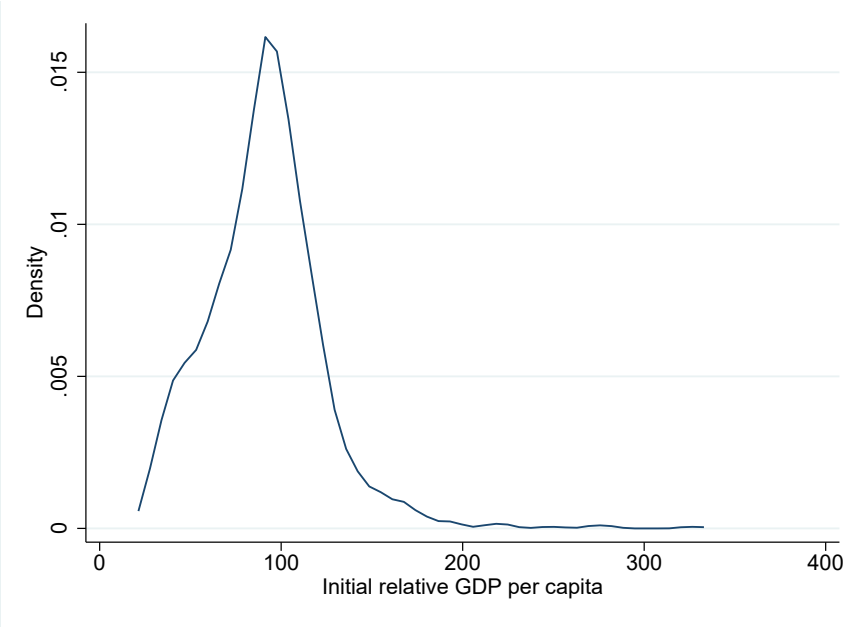


Figure D.3: **Density function of the forcing variable**

Notes: The figure shows the distribution of initial relative GDP per capita. Data for all five funding periods are pooled.
Sources: Eurostat; own illustration.

E Validity

In this section, we provide evidence for the validity of the RD Design. First, we show that the forcing variable is smooth around the cutoff. We then test for manipulation for each funding period separately. Finally, we examine the covariates for discontinuities at the eligibility cutoff.

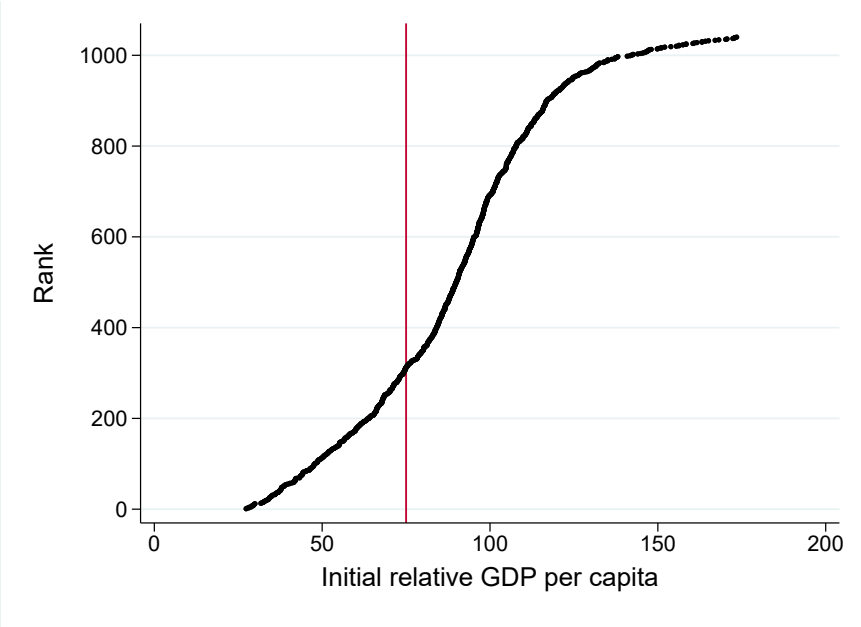


Figure E.4: **Ranking of regions based on initial relative GDP per capita**

Notes: The figure shows regional initial GDP per capita relative to the EU average in ascending order. Data for all five funding periods are pooled.
Sources: Eurostat; own calculations and illustration.

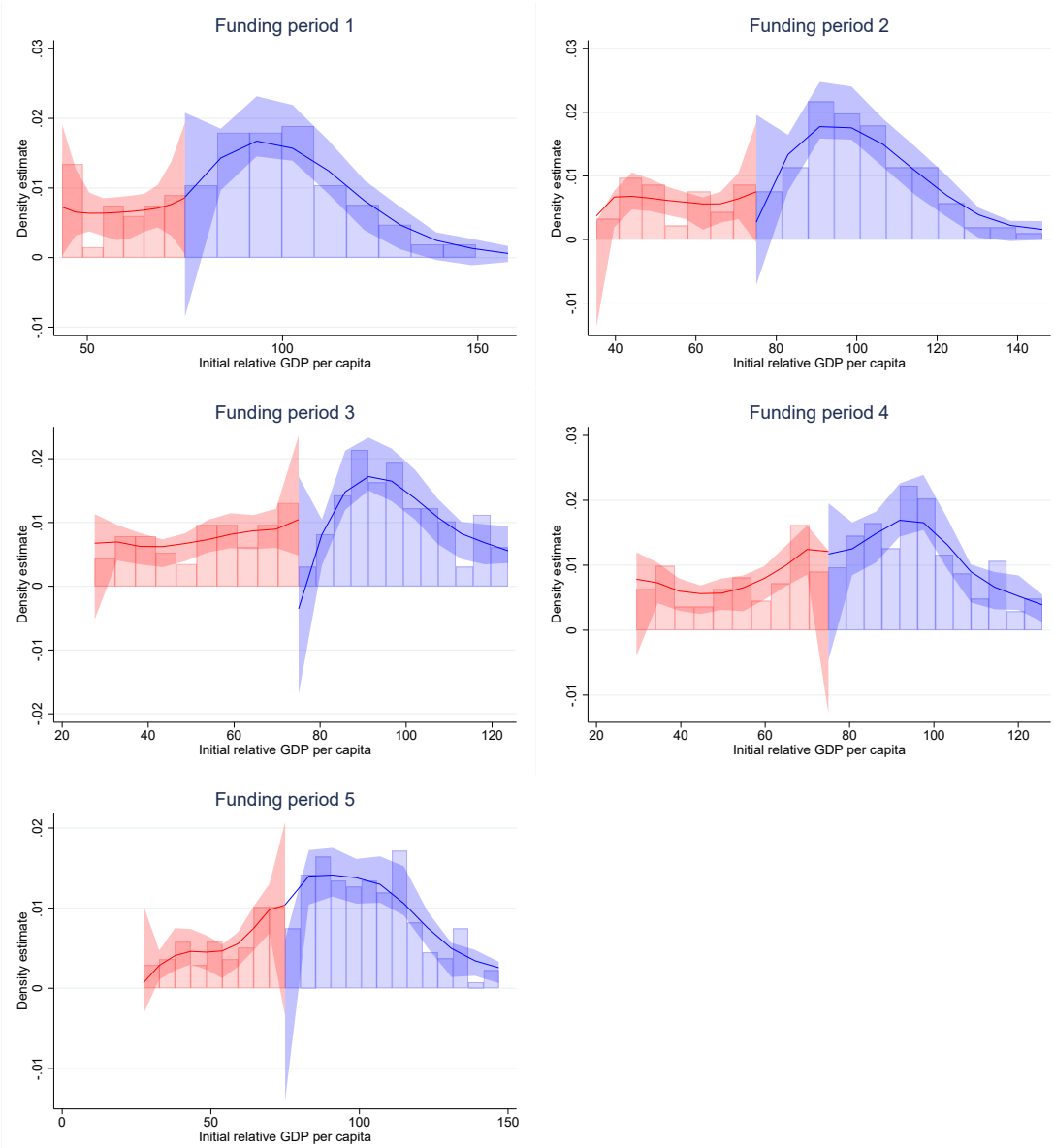


Figure E.5: **Manipulation testing**

Notes: Testing manipulation using density estimation for the forcing variable. For funding period 3, we pool data for the EU-15 countries and the new Member States joining the EU in 2004, although the forcing variable is calculated over different years (see Table 2).
Sources: Eurostat; illustration: Cattaneo et al. (2018).

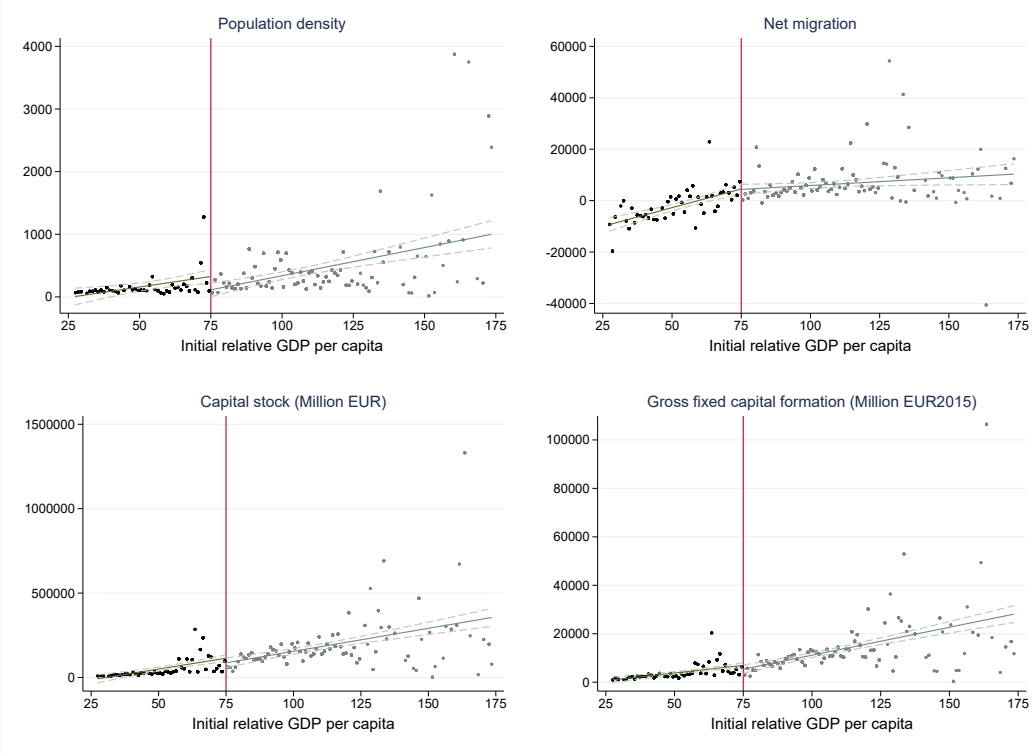


Figure E.6: **Continuity of covariates: Demographics and Capital resources**

Notes: The figure shows variables capturing the demographics and capital endowment of European regions in equally sized bins of 1 percentage point which are plotted against the forcing variable for regions with an initial relative GDP per capita up to 175 % of the EU average. Always-takers are excluded. Data for funding periods 3-5 are pooled.
Sources: Eurostat, ARDECO; own calculations and illustration.

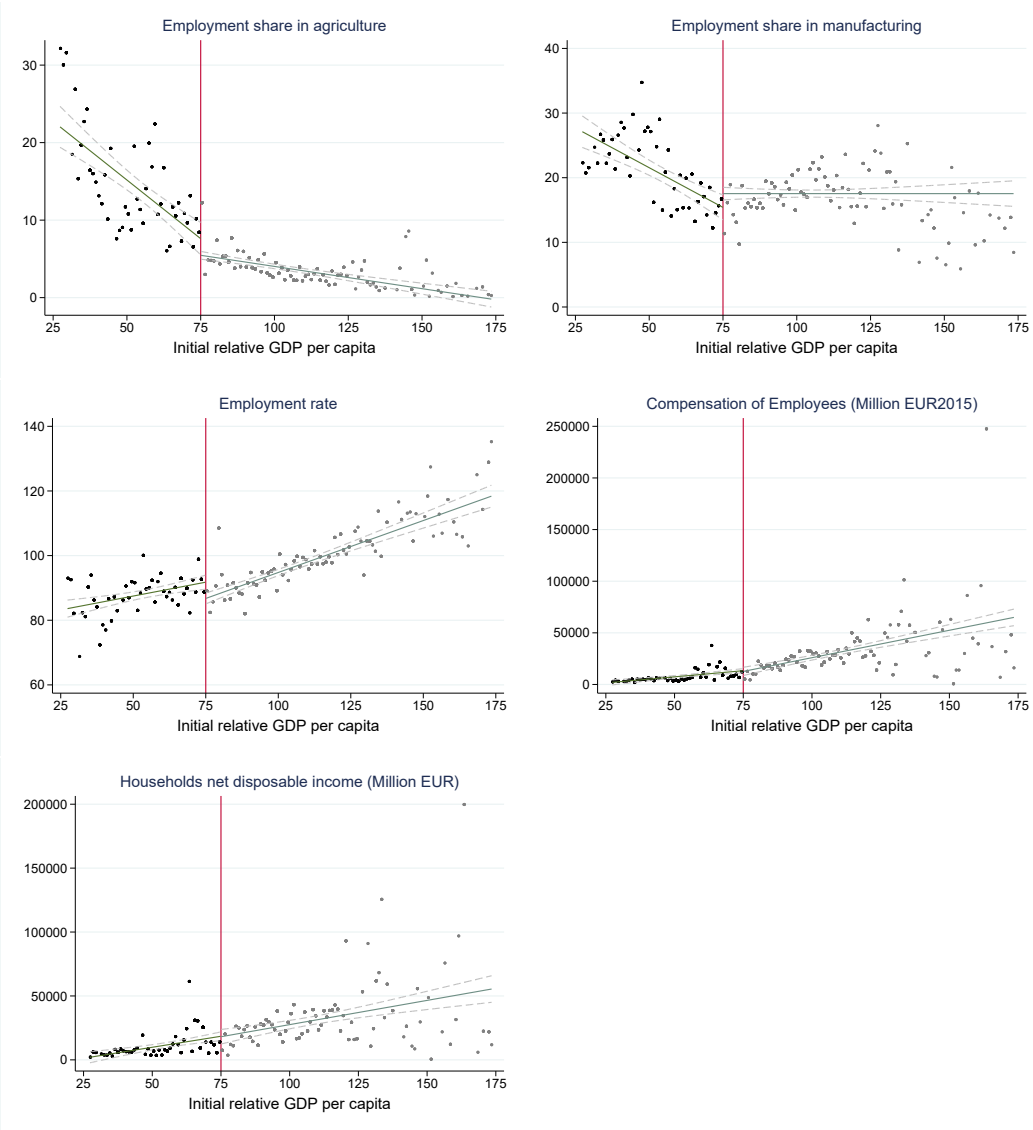


Figure E.7: **Continuity of covariates: Labor Market and Household Income**

Notes: The figure shows variables capturing labor market conditions and household income in European regions in equally sized bins of 1 percentage point which are plotted against the forcing variable for regions with an initial relative GDP per capita up to 175 % of the EU average. Always-takers are excluded. Data for funding periods 3-5 are pooled.
Sources: Eurostat, ARDECO; own calculations and illustration.

F Sensitivity checks

Figure F.8 shows that allowing for period-specific functional forms of the forcing variable in addition to period dummies fits the data better.

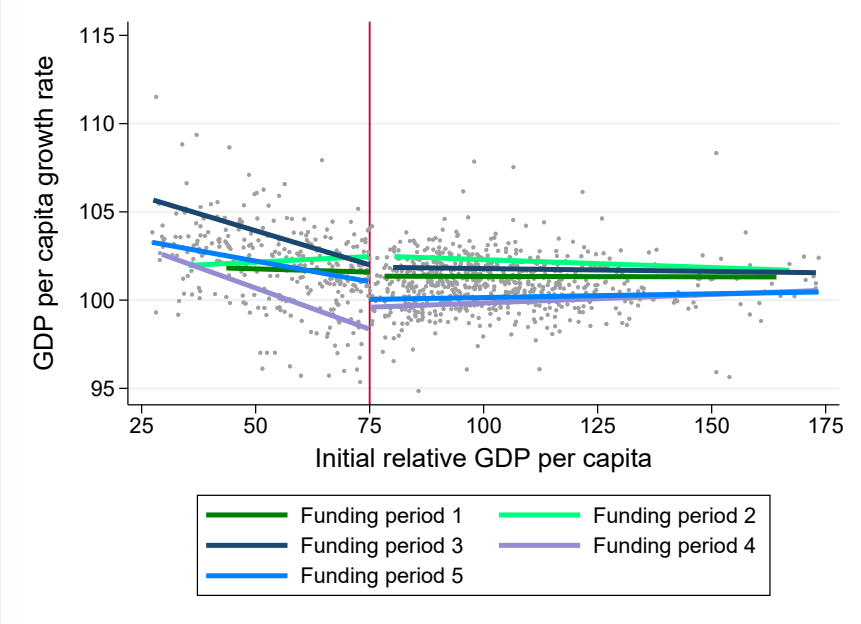


Figure F.8: **Functional form of the forcing variable**

Notes: The figure shows average annual GDP per capita growth rates over a funding period which are plotted against the period-specific forcing variable for regions with an initial relative GDP per capita up to 175 % of the EU average. Always-takers are excluded.
Sources: Eurostat, ARDECO; own calculations and illustration.

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