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721/2026

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Alexander Daminger
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WIFO Working Papers 721/2026
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E-Mail: alexander.daminger@wifo.ac.at, peter.huber@wifo.ac.at, klaus.nowotny@wifo.ac.at

2026/1/W/24098

Media owner (publisher), producer: Austrian Institute of Economic Research
1030 Vienna, Arsenal, Objekt 20 | Tel. (43 1) 798 26 01 0 | https://www.wifo.ac.at
Place of publishing and production: Vienna

Free download: https://www.wifo.ac.at/publication/pid/67172012

Counterfactual Impact Evaluation of Cohesion Policy 2014-2020

Regression Discontinuity Design

Alexander Daminger, Peter Huber, Klaus Nowotny[1]

Study Commissioned by the Directorate-General for Regional and Urban Policy (DG REGIO), Directorate B — Policy, Unit B.1 — Policy Development and Evaluation, under contract number 2024CE16BAT058.

Abstract

This study evaluates EU Cohesion Policy interventions during 2014-2020 using regression discontinuity design (RDD), exploiting funding thresholds at 75% and 90% of EU average GDP per capita across 281 NUTS-2 regions. The analysis examines nominal and real GDP per capita growth, GDP per capita at purchasing power standards, and employment and unemployment changes. Contrary to earlier programming periods, the study finds no statistically significant discontinuity in treatment intensity near the cutoff thresholds under conventional RDD specifications with flexible functional forms and optimal bandwidth estimators. While marginally significant positive effects on real GDP growth emerge under restrictive assumptions, results lack robustness across model specifications. Pretests reveal potential structural breaks in other causal variables at the cutoffs. The findings provide descriptive evidence of positive correlations between regional development and cohesion policy but fail to establish robust causal links. This limitation likely stems from institutional changes during 2014-2020, including transition region introduction and modified allocation criteria that reduced funding discontinuity sharpness, or from pandemic-driven regional shocks.

Key Words: Regional Policy, GDP Growth, Employment and unemployment, Evaluation

JEL-Codes: R11, M13, C21, L11

[1] The authors thank Julia Bachtrögler, Davide Ceccanti, Tillmann Heidelk, Philippe Monfort, and Hannes Winner for helpful comments.

Contents

Executive summary

This paper offers an in-depth quantitative assessment of the European Union's Cohesion Policy interventions during that programming period. Using a regression discontinuity design (RDD). It thus aims to estimate the causal effects of policy funding on regional macroeconomic outcomes. This method exploits distinct eligibility thresholds at the 75% and 90% cutoffs in GDP per capita relative to the EU average, that determined the intensity of Cohesion Fund support for NUTS-2 regions.

The primary objective of EU Cohesion Policy is to foster balanced development by reducing regional disparities. Traditionally, the most critical variable for determining eligibility and the intensity of funding has been a region's GDP per capita expressed in purchasing power standards (PPS). Under this scheme, regions are classified into three categories: less developed (GDP <75% of EU average), transition (GDP between 75% and 90%), and more developed (>90%). However, during the 2014–2020 period, several institutional changes altered the policy landscape in ways that challenged the premise of a clear treatment threshold around these cutoffs.

Notably, the allocation of funds in 2014–2020 was influenced not only by GDP per capita but also by an increasingly complex set of additional variables. These included regional indicators such as unemployment rates (especially youth unemployment), education attainment levels, and the regional impact of exceptional shocks like the COVID-19 pandemic—a consideration especially relevant for REACT-EU funds. Moreover, eligibility for the Cohesion Fund was determined at the national level, being limited to Member States whose Gross National Income (GNI) per capita did not exceed 90% of the EU average. A cap of 2.5% of national GDP also limited maximum annual allocations, introducing additional constraints that complicated the relationship between GDP thresholds and funding intensity.

These institutional features affected the empirical sharpness of the policy thresholds, posing significant limitations for RDD analysis. While previous studies demonstrated relatively sharp discontinuities in funding around the GDP thresholds and used these discontinuities to, as a rule, establish positive effects of EU Cohesion Policy on GDP Growth and other outcome variable, this paper found no statistically significant jumps in actual treatment intensity at either the 75% or 90% cutoffs—except under restrictive modelling assumptions, such as applying linear forms with broad bandwidths that conflict with best practices.

As a consequence, the core RDD identification strategy produced largely inconclusive or non-robust results. Weak instrument relevance in the fuzzy RDD framework further undermined the ability to derive causal estimates of program impact. Even when treatment effects appeared marginally statistically significant—for example, higher growth rates or declining unemployment in less developed regions—they did not hold across different specifications and tended to be significant only at the 10% level.

The paper thus argues that this lack of "sharpness" in the application of GDP thresholds is likely due to changes in policy design, such as the introduction of transition regions, and the expanded use of variables beyond GDP used for fund distribution. These factors likely diluted the discontinuity expected at the eligibility cutoff points, leading to overlapping distributions of funding levels and regional characteristics.

Pretests also revealed structural breaks at the thresholds in variables known to influence regional growth—such as sectoral composition, age distribution, and education levels—raising concerns that any observed outcome differences could be driven by these confounding factors rather than funding status alone. Moreover, the statistical power of the paper is constrained by the relatively small number of NUTS-2 regions and the limited post-treatment observation period, which was further shortened to account for the disruptive effects of the COVID-19 pandemic.

In summary, while this paper reaffirms a general positive correlation between Cohesion Policy funding and regional development, it fails to establish robust causal impacts for the 2014–2020 cycle. The diluted role of GDP per capita and increased weight of additional socio-economic and demographic indicators introduces important implications for future policy evaluations. Specifically, these findings suggest that evaluators will need to adopt more sophisticated identification strategies that can account for the multidimensional criteria now shaping Cohesion Policy distributions. This will likely require broader samples, longer observation periods, and potentially smaller territorial units (such as NUTS-3 regions) to increase statistical power and improve inference.

1. Introduction

Under the 2014-2020 multiannual financial framework, cohesion policy accounted for about one third of European Union (EU) funding. The purpose of the cohesion policy funding is to reduce disparities between the levels of development of the various regions and reduce the backwardness of the least favored regions by investing, among others, in job creation and a sustainable and healthy European economy and environment. These interventions were co-financed by the European Regional Development Fund (ERDF), the European Social Fund and the Recovery Assistance for Cohesion and the Territories of Europe (ESF and REACT-EU), and the Cohesion Fund (CF) and were programmed under eleven thematic objectives including strengthening research, technological development and innovation, the competitiveness of small and medium-sized enterprises (SME), network infrastructures in energy and transport, as well as sustainable and quality employment, social inclusion, and the low-carbon economy. The Regulations of the Funds were amended to include specific provisions that addressed the immediate and longer-term impacts of the Covid-19 pandemic (CRII and REACT-EU) and the consequences of the military aggression of Russia against Ukraine (CARE and Fast-CARE). The large majority of cohesion policy funding is received by less developed NUTS-2 regions, i.e., regions with a GDP (Gross Domestic Product) per capita below 75% of the EU average.

The current paper conducts a quantitative evaluation of the impact of EU Cohesion Policy interventions during the 2014-2020 programming period on regional macroeconomic development. To identify the causal effects of these regional policies, we build on previous contributions (e.g., Becker et al., 2010, 2012; Pellegrini et al., 2013; Ferrara et al., 2017; Percoco, 2017) and apply a regression discontinuity design (RDD) approach. This method leverages the fact that funding varies significantly between regions with GDP per capita at purchasing power parity (PPP) below and above 75% and 90% of the EU average. We analyze five key outcome variables: nominal and real GDP per capita growth, GDP per capita at PPS, as well as changes in employment and unemployment rates. To mitigate potential contamination of our results by the COVID-19 crisis, we focus on two periods of analysis: 2014-2020 and 2014-2019, where the later period is chosen to filter out the impact of the COVID-19 pandemic in 2020.

While prior Regression Discontinuity Design (RDD)-based evaluations have predominantly examined multiple programming periods collectively (e.g., Bachtrögler, 2016; Becker et al., 2018; Cerqua & Pellegrini, 2022; Lang, 2023) or focused on NUTS-3 level data (e.g., Gagliardi & Percoco, 2016), this paper, to the best of our knowledge, is the first to exclusively examine the 2014-2020 programming cycle using NUTS-2 level data. This temporal specificity is particularly relevant given the institutional changes introduced during this period, such as the implementation of transition regions and the n+3 rule for fund absorption.[2] However, this narrower focus also presents methodological challenges, including a smaller number of observations and limited post-treatment data points.

Contrary to findings from earlier programming periods, we find no statistically significant discontinuity in treatment intensity – measured as EU funding per capita or GDP – near the 75% and 90% thresholds. Statistically significant variations in treatment intensity at these thresholds only emerge under restrictive assumptions, such as including observations farther from the cutoff or imposing linear functional forms. Under these conditions, we observe marginally significant positive effects on real GDP growth (2013-2020), as well as positive effects on employment and unemployment rates in some specifications. However, these effects are not robust across model specifications. When applying more flexible functional forms, conventional weighting schemes for observations, or standard bandwidth choices aligned with best practices in RDD design, most results lose statistical significance.

This paper therefore provides descriptive evidence of a positive correlation between regional development and cohesion policy interventions but does not establish robust causal links regarding the impact of structural funds. This limitation may stem from the paper's exclusive focus on a single programming period, which differs significantly from earlier cycles in terms of policy design and was further shaped by regionally uneven shocks from the COVID-19 pandemic. They may, however, also be due to institutional differences in the mechanisms determining funds allocation in the 2014 to 2020 period relative to previous funding periods, as these may have reduced the "sharpness" of the fund allocation. Irrespective of the reason for our findings this suggests that future evaluations of Cohesion Policy will also have to carefully scrutinize the validity of identification assumptions used to identify RDDs, particularly as eligibility criteria evolve.

The remainder of the paper is structured as follows: Section 2 describes the specifics of the program under evaluation. Section 3 outlines the overarching methodological approach and details its central identification assumptions and Section 4 presents the data used. Section 5 presents a series of pretests assessing these assumptions, while Section 6 discusses the estimation results. Section 7 reports additional robustness checks and extensions, followed by concluding remarks in Section 8.

(2) In the 2014 – 2020 period all funds had to be spent at least three years after the end of the programming period (the so-called n+3 rule), while previously it was two years.

2. The specifics of EU regional policies (from an evaluation perspective)

The majority of cohesion policy funding in the 2014–2020 period was allocated according to a scheme in which the EU's NUTS-2 regions were classified into three categories:

- Less developed regions, whose Gross Domestic Product (GDP) per capita was less than 75% of the EU-27 average,
- Transition regions, whose GDP/capita ranged between 75% and 90% of the EU-27 average, and
- More developed regions, whose GDP/capita exceeded 90% of the EU-27 average.

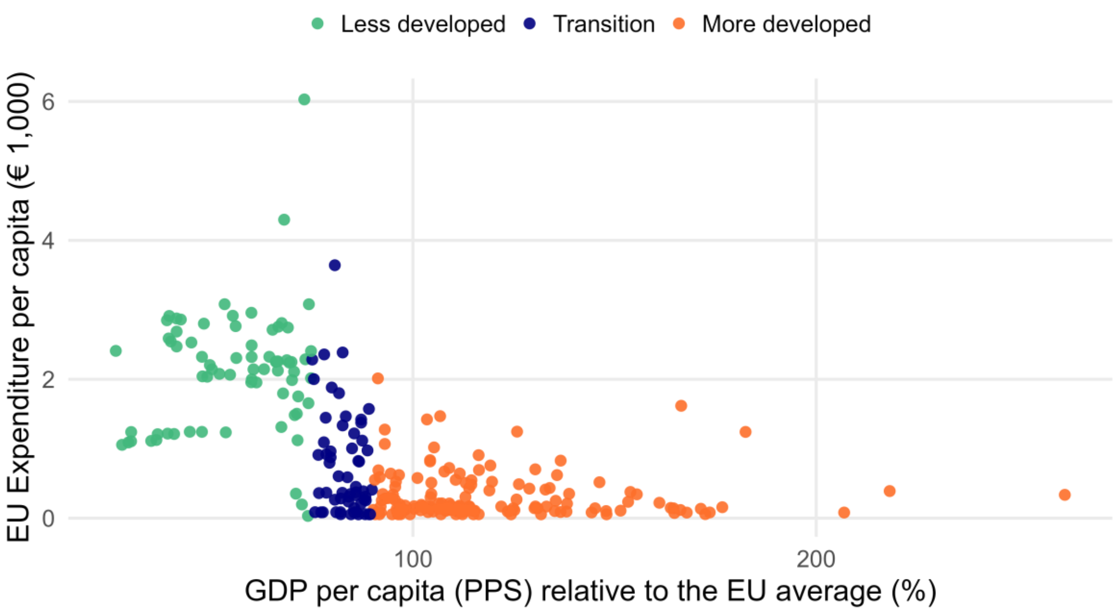
While the largest share of funds was directed toward less developed regions, both transition and more developed regions were also eligible for funding. Regional income, however, was not the only funding criterium. Further criteria (e.g. unemployment, youth unemployment, educational attainment level and in the case of REACT-EU also the severity of the COVID-19 crisis) entered the decision rule for regional funds allocation (see ECA, 2019) and eligibility for the Cohesion Fund was determined at the member state level: only member states whose Gross National Income (GNI) per capita did not exceed 90% of the EU-27 average were eligible for funding (see European Commission, 2015). In addition, maximum eligibility was limited to 2,5% national GDP per year (see European Parliamentary Research Service, 2013).[3]

Figure 1 therefore plots EU expenditure per capita[4]) during the 2014 to 2020 period against the average GDP per capita at PPS (for the years 2007 to 2009), measured at NUTS-2 regional level. It suggests that lower levels of initial GDP per capita were associated with higher levels of per capita EU funding. Less developed regions appear to have received more funding than transition regions, which in turn received higher per capita funding than more developed regions.

([3]) The allocation methodology for different funds and region types was detailed in ANNEX VII of European Parliament and Council (2013). According to this regulation for less developed and transition regions unemployment was an additional relevant additional factor for fund allocation. For more developed regions also education, employment, and demographics affected the allocation. For the youth employment initiative the level and growth of youth employment and for ESF funding employment rates were relevant, while funding from EU-REACT sources was additionally affected by the loss of GDP in 2019 (see European Parliament and Council 2013, pp 186 -190)

([4]) We focus on the total expenditure of the cohesion fund, the ERDF, the youth employment initiative the ESF as well as REACT funds. The EU expenditure is the sum distributed by the commission excluding any co-financing by the member states.

Figure 1 – EU Expenditure and GDP per capita by region type



Source: DG-Regio, ARDECO; WIFO-calculations.

Figure excludes the outlier of Inner London (UKI3 with a per capita GDP of 565.6% of the EU average)

Table 1: Funds per capita received by different region types (in 1,000 EUR)

	Less developed regions	Transition regions	More developed regions
Total EU Expenditure	2.00	0.72	0.30
	Expenditure by Fund		
Cohesion Fund	0.40	0.06	0.02
ERDF (excluding REACT-EU)	1.04	0.38	0.10
Youth employment initiative	0.02	0.02	0.02
ESF (excluding REACT-EU)	0.40	0.17	0.07
REACT-EU	0.13	0.10	0.08
	Expenditure by Category		
Aid to Private Sector	0.20	0.06	0.03
Human Capital	0.47	0.22	0.13
Infrastructure	0.55	0.23	0.07
RTD	0.27	0.12	0.04
Technical Assistance	0.06	0.02	0.01
Transport	0.45	0.08	0.02

Source: European Commission, ARDECO, WIFO-calculations.

Regions are categorized based on their average GDP at PPS for the years 2007 to 2009 in % of the EU average: <75% = "Less developed regions"; ≥ 75% & <90% = "Transition regions"; ≥90% = "More developed regions".

Table 1 augments this information by providing the population-weighted average funding per capita – both in total and disaggregated by fund, expenditure purpose as well as region type. In accordance with the program's design, less developed regions received substantially higher EU funding per capita than transition regions across all funds and expenditure categories. In total, EU funding to these regions amounted to EUR 2,000 per capita, while transition regions received EUR 700 per capita. More developed regions received only EUR 300 per capita. As expected, given the different regulations governing the various funds, these differences are most pronounced in the Cohesion Fund and the European Regional Development Fund (ERDF). Similarly, per capita expenditure differences are noticeably larger for infrastructure investments than for other expenditure categories. This can likely be explained by the different mix of funding sources in these regions[5]), as well as lower levels of existing infrastructure endowments, and therefore greater investment needs in less developed regions.

3. Evaluation Method

To provide causal results based on an established evaluation method, we propose identifying the treatment effects of regional policy by exploiting the variation in treatment intensity at the 75% and 90% GDP per capita levels implied by the policy design. Specifically, we follow previous contributions to the literature evaluating EU regional policies (e.g., Becker et al., 2010; Pellegrini et al. 2013; and Pellegrini, 2016) and use these cutoff levels in a Regression Discontinuity Design (RDD). One advantage of this method is that it is a well-understood and widely used identification strategy, which has also been applied in earlier studies. This facilitates comparability of results across intervention periods. A further advantage is that the method primarily relies on cross-sectional variation in the data and thus minimizes concerns related to repeated treatments.

However, one disadvantage of the RDD approach is that it only allows for an identification of local average treatment effects – that is, the effects of funding for regions just below the cutoff point relative to regions just above the cutoff. For regions located farther from the cutoffs (e.g., very poorly developed, or extremely well-developed regions), the estimated effects may not be applicable. Another disadvantage is that RDD is a data demanding method and its ability to identify causal effects hinges on the crucial assumption that the probability of treatment (if binary) or the expected value of treatment (if continuous, as in our case) exhibits a discontinuous "jump" at the cutoff. In an ideal statistical application, this would require a large number of observations just above and just below the cutoff. However, this is unlikely to hold for the EU NUTS-2 regions. In total, including the UK, there are only 281 such regions of which 73 were classified as less developed, 50 as transitional, and 158 as more developed in the 2014 to 2020 period.

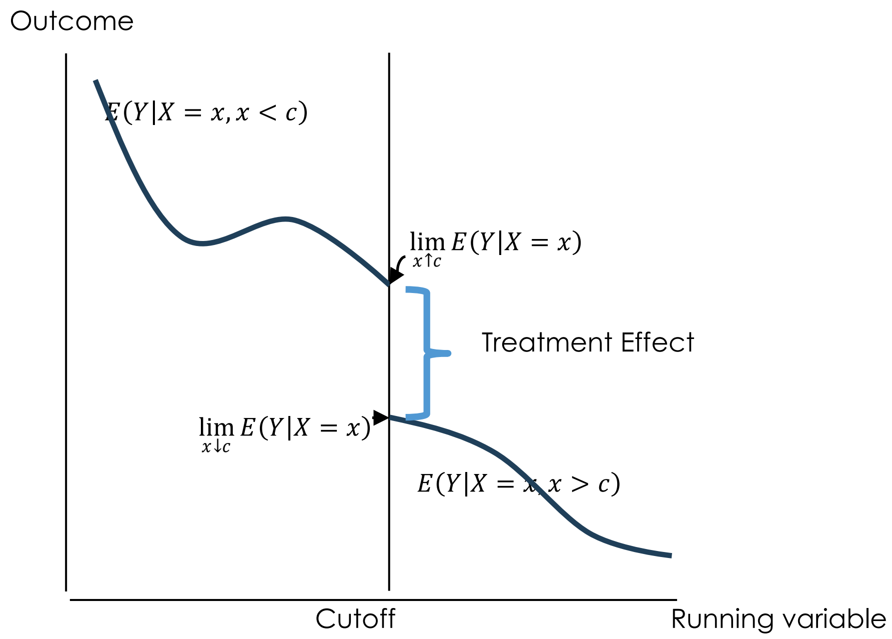
([5]) In less developed regions slightly more than 50% of the expenditure was financed by the ERDF, in more developed regions this was less than a third.

Consequently, to conduct meaningful statistical analyses, we will have to include observations located further from the cutoff, although they are less suitable for identifying effects precisely at the threshold. This, in turn, introduces substantial methodological challenges, which are discussed in detail below.

3.1. Sharp RDD

RDD uses the fact that regions with a GDP per capita just below the 75% (respectively the 90%) cutoff are likely to have been rather similar to regions just above this cutoff but have experienced a substantial difference in their exposure to the treatment. Thus, regions just below the cutoff are likely to be considered a good comparison group to regions just above the cutoff.

Figure 2: A prototypical RD-Design



Source: WIFO-illustration.

Formally, the Regression Discontinuity Design (RDD) relies on two key components: (1) a running (or score) variable X, which in our case is GDP per capita at purchasing power standards (PPS), and (2) a cutoff value c, which in our context corresponds to 75% and 90% of the EU average GDP. This defines the value of the running variable at which (more intense) treatment applies. The central idea is that, given these components, the expected outcome Y for a region located just below the cutoff – denoted by $\lim_{x \uparrow c} E(Y|X = x)$, with $x \uparrow c$ indicating estimation from below the cutoff – and the expected outcome for a region located just above the cutoff – denoted by $\lim_{x \downarrow c} E(Y|X = x)$, with $x \downarrow c$ indicating estimation from above – can be estimated. Consequently, if treated units have no discretion over their treatment and treatments are uniform across units to the left of the cutoff, the local average treatment effect (LATE) of the policy can be estimated by (see Hahn, Todd and van der Klaauw, 2001 for a detailed proof):

$$\tau = \lim_{x \uparrow c} E(Y|X = x) - \lim_{x \downarrow c} E(Y|X = x) \qquad (1)$$

Figure 2 shows a graphical representation of this approach. The vertical axis measures the outcome while the horizontal axes measures the running variable. The horizontal line at point c on the vertical axis represents the cutoff. Furthermore the (cubic) functions to the left and right of the cutoff – denoted by $E(Y|X = x, x < c)$ and $E(Y|X = x, x > c)$ respectively – represent estimates of the expected outcome as a function of the running variable on either side of the cutoff. Consequently, the points marked by $\lim_{x \uparrow c} E(Y|X = x)$and $\lim_{x \downarrow c} E(Y|X = x)$ are the respective expected values at the cutoff c, and the vertical difference between them is the local average treatment effect (LATE).

One of the central topics in RDD analysis is the method used to estimate the limits of the expectation functions $E(Y|X = x, x < c)$ and $E(Y|X = x, x > c)$. In the simplest case, this can be done by using a linear regression model that allows for different slope parameters for the running variable on the left and the right of the cutoff, denoted by $\beta_{x<c}$ and $\beta_{x>c}$ respectively. In this case, the baseline specification for an RDD is (see Lee and Lemieux, 2010; Cattaneo, 2022):

$$Y_i = \alpha + \tau D_i + \beta(X_i - c) + \gamma(X_i - c)D_i + \varepsilon_i \qquad (2)$$

D_i is an indicator variable for all regions to the left of the cutoff and τ is the estimated local average treatment effect.

However, many authors have argued that this may be an overly simplistic approach and have advocated for using:

- higher order polynomials of the variable $(X_i - c)$ both on the left and the right of the cutoff when estimating Equation (2), to account for potential non-linearities between the running variable and the outcome.

- only observations "close" to the cutoff by using an appropriately chosen bandwidth on the left and right of the cutoff and/or by giving greater weight to observations near the cutoff through kernel weighting, as observations far from the cutoff may be uninformative for the value of the expectation function at the cutoff.

Indeed, a recent survey by Cattaneo, Idrobo, and Titiunik (2019) suggests that the baseline specification of a RDD analysis should be based on Equation (2), using an optimal bandwidth (determined by a mean squared error criterion) and a triangular kernel weight for observations and should also demonstrate the robustness of results with respect to different functional forms of Equation (2).

Another central issue in RDD analysis is the plausibility of the method's identification assumptions. For a causal interpretation of a sharp RDD, the following assumptions must hold: First, regional units must not be able to precisely manipulate the forcing variable. Second, there should be no equivalent jumps in other causal determinants of the outcome at the same GDP/capita cutoff levels Third, the Stable Unit Treatment Value Assumption (SUTVA), which states that there are no externalities or spillovers between regional units, must be fulfilled.

In empirical applications of RDD, it has therefore become standard practice to examine whether “bunching“ (i.e., an accumulation of units) occurs just below (or above) the cutoff. Such a pattern may indicate manipulation of the running variable. Formal methods to test for this have been proposed by McCrary (2008) and Cattaneo, Jansson and Ma (2020). Furthermore, RDD applications often include placebo tests for other potential confounding discontinuities by running similar RDD analyses on alternative outcome or control variables (see, for example, Cunningham, 2021, Chapter 6).

3.2. Fuzzy RDD

As stated above, the sharp RDD design applies only to cases where the treatment status or intensity is a deterministic function of the running variable (Cunningham, 2021) and where the treated units have no autonomy over whether to take the treatment or not (i.e., are compliers). However, both of these conditions do not hold in the case of EU regional policies. Rather than turning a uniform treatment on or off, crossing the 75% or 90% cutoff in GDP per capita affects the potential intensity of the treatment – i.e., the expected amount of funding received from the Cohesion Fund, per capita. In addition, as the regions eligible for funding were also responsible for implementing the program, regional authorities received some leeway whether they use all funds or not.

In this case, the sharp RDD only identifies the so-called “intention-to-treat“ effect rather than the treatment effect proper (i.e., the impact of providing access to regional funds, rather than the impact of actual payments). It is reasonable to expect that this “intention-to-treat“ effect is closely related to the actual treatment effect, and we will discuss this effect further in the results section below.

Nonetheless, the interest of the current paper is the causal impact of structural funds expenditure. As pointed out, inter alia, by Cattaneo, Idrobo and Titiunik (2019), this requires the use of a “fuzzy“ RDD. This is a very similar approach to the sharp RDD but treats the cutoff as an “instrument” for expected treatment intensity. Essentially, this implies that, in a first-stage regression an “expected treatment intensity” is estimated for the units left and right of the cutoff, in a manner similar to the sharp RDD. This predicted intensity is then used as an explanatory variable in a second-stage estimation.

More formally, a fuzzy RDD can be estimated using instrumental variable (IV) methods, such as two-stage least squares (2SLS). The first stage of such a fuzzy RDD estimates the effect of crossing the cutoff – serving as the instrument – on the intensity of the treatment T:

$$T_i = \gamma + \phi D_i + \delta(F_i - c) + \mu(F_i - c)D_i + \eta_i \tag{3}$$

The predicted values of the treatment intensity from this estimation, $\widehat{T_i}$, are then included in the second stage that estimates the effect of treatment intensity on the outcome variable:

$$Y_i = \alpha' + \lambda\widehat{T_i} + \beta'(F_i - c) + \gamma'(F_i - c)D_i + \epsilon_i \tag{4}$$

The coefficient λ can then be interpreted as the "local-average-treatment-effect" (LATE) of T – that is, the causal effect of cohesion policy funding on the outcome variable at the cutoff for those regions whose treatment intensity is affected by being below the cutoff (i.e., the compliers).

As with the sharp RDD, the estimation of a fuzzy RDD raises issues related to potential nonlinearities in the estimation function, the choice of appropriate bandwidths, as well as weighting of observations. Likewise, Cattaneo, Idrobo, and Titiunik (2019) suggest that, also for a fuzzy RDD analysis, the baseline specification should be based on optimal bandwidth estimators using a triangular kernel for observation weights, and that specifications should be tested for their robustness with respect to different functional forms.

Furthermore, due to the instrumental variable method used in the fuzzy RDD, this approach is even more data demanding than the sharp RDD and imposes additional identification assumptions. Specifically: (i) the instrument (i.e., the cutoff levels) must be relevant for treatment intensity (i.e., the funds received); but (ii) it must not affect the outcome except through its effect on funding (the so-called "exclusion restriction"); and (iii) the "independence" assumption requires that the instrument be "as good as randomly" assigned – that is, independent of the potential value of the outcome variable a treated region would have had in the absence of treatment. While assumptions (ii) and (iii) cannot be tested empirically, they appear plausible given the specific cutoff levels are, in essence, arbitrary. Assumption (i), however, can be tested by examining the significance of the instrument D_i in the first-stage regression (3).

4. Data

We use data from three different sources to implement the regression discontinuity design outlined above. The first is payment data provided by the European Commission. This dataset, calculated by DG-REGIO, provides information on the EU's expenditure by NUTS-2 region disaggregated by fund, by type of use and in total (see Figure 1 and Table 2 for descriptive statistics). In cases where expenditures could be directly allocated to NUTS-2 regions, the data reports exact amounts. Where this was not possible, (e.g., in case of national programs), the expenditures were distributed on a per capita basis across regions within the respective country. [6]

The second and third data source are ARDECO and EUROSTAT. From the ARDECO database[7]), we extracted the following indicators for the years 2013 and 2020:

- average population,
- GDP per capita at current prices,
- GDP per capita at constant prices,
- GDP per capita at purchasing power parities, and
- the employment rate (i.e., employment relative to population).

In addition, we collect further variables from ARDECO to check for structural breaks in factors potentially correlated with regional economic development. These variables include the gross value added (GVA) at current prices by industry (10 sectors), and employment by industry (10 sectors).

From Eurostat, we collected additional data on the unemployment rate (used as an additional outcome variable), as well as data on population by highest completed education[8]) and by age group (below 15 years, 15 to 64 years, and 65 years or older). These variables have been shown to impact GDP growth and/or unemployment and employment.

Finally, the classification of regions as less developed, transition or more developed was based on average GDP per capita at PPS for the years 2007 to 2009, expressed as percentage of the EU average, as it was estimated at the time of the program's design according to Article 90(2) of the Common Provisions Regulation for the European Structural and Investment Funds (Regulation (EU) 1303/2013). For this reason, we requested vintage estimates of GDP at PPS from Eurostat. These are used both as a running variable and to design the cutoff in the analysis below.

The datasets differ slightly in terms of scope and coverage. Thus, for GDP and GVA indicators, data are available for all EU regions, including the United

([6]) We focus on NUTS 2 regions because due to the availability of reliable funding data at this level.

([7]) "The Annual Regional Database of the European Commission (ARDECO)" provides consistent and harmonised timeseries of demographic and socio-economic statistical data at the regional and sub-regional levels, see https://urban.jrc.ec.europa.eu/ardeco/explorer

([8]) In detail these indicators are the share of the less educated (ISCED 2 or lower), middle education (ISCED 3 and 4) and high educated (ISCED 5 or more) residing in a region.

Kingdom. By contrast, for employment and unemployment rates, data for the UK are missing (as well as for the Aland Islands, FI20, in the case of the unemployment rate). Furthermore, some changes occurred in the NUTS-2 classification during the programming period. We therefore used the "NUTS converter" [9]), a conversion tool developed by the Joint Research Centre (JRC) to consistently recode all values to the NUTS 2016 classification.

From these raw data, we calculated five outcome indicators. These are:

- Percentage growth of nominal GDP per capita over the period 2013 to 2020,
- Percentage growth of real GDP per capita over the period 2013 to 2020,
- Percentage growth of GDP per capita at purchasing power parity between 2013 and 2020,
- Percentage point change in the employment rate between 2013 and 2020, and
- Percentage point change in the unemployment rate between 2013 and 2020.

One concern with respect to these indicators is that they include data extending into the COVID-19 pandemic in 2020. The measures taken to limit this pandemic led to a massive economic crisis that affected the member states and their regions to varying degrees. Consequently, basing causal estimates on the period 2013 to 2020 runs the risk of contaminating results with the regional impact of the COVID-19 pandemic. Therefore, as a robustness check, we additionally conducted sharp and fuzzy RDD analyses for the outcome variables measured in terms of changes between 2013 and 2019.

Table 2 reports unweighted sample means and standard deviations for each indicator, for all 281 NUTS-2 regions of the EU (including the UK), and for the 240 NUTS-2 regions excluding the UK. It also provides statistics by region type, distinguishing less developed, transition, and more developed regions. In addition, for transition and less developed regions, the right-hand panel also reports results of t-tests for the equivalence of means of the respective region types.[10])

For example, the first row of the table states that in the average NUTS-2 region GDP per capita increased by 16.3% from 2013 to 2020, with this growth amounting to 25.9% in less developed regions, on average. Furthermore,

(9) The "NUTS Converter" is an open, web-based tool enabling the conversion of European regional statistical data between different versions of the Nomenclature of Territorial Units for Statistics (NUTS) classification (Joint Research Centre, 2022). We use a package adoption for R (Hennicke – Krause, 2024).

(10) Thus, the column labelled (2)=(1) reports results of a t-test for equivalent means of less developed and transition regions, the column labelled (3)=(1) for equivalence of means of less developed and more developed regions, and the column (2)=(3) for equal means of transition and more developed regions.

according to the left-hand panel, both transition and more developed regions experienced statistically significantly slower growth – of 12.0% and 12.5%, respectively – compared to less developed regions. However, the difference between transition and more developed regions was only marginally significant at the 5% level.

Table 2: Descriptive statistics for outcome variables used in the analysis.

	Overall	Less developed	Transition	More developed	T-tests for equality of means(columns)		
		(1)	(2)	(3)	(2)=(1)	(3)=(1)	(2)=(3)
Growth of GDP per capita at PPS 2013/2020	16.34 (15.81)	25.85 (16.08)	11.98 (9.98)	12.54 (15.12)	***	***	*
Growth of GDP per capita at PPS 2013/2019	20.58 (13.1)	28.10 (13.1)	18.36 (8.5)	17.15 (12.8)	***	***	
Growth of real GDP per capita 2013/2020	7.06 (14.7)	15.25 (13.3)	3.06 (9.7)	3.87 (15.1)	***	***	**
Growth of real GDP per capita 2013/2019	13.20 (12.2)	20.36 (11.3)	10.86 (9.1)	10.02 (12.1)	***	***	
Growth of nominal GDP per capita 2013/2020	18.43 (19.5)	30.78 (20.6)	12.50 (12.5)	13.61 (17.9)	***	***	**
Growth of nominal GDP per capita 2013/2019	22.98 (17.2)	34.14 (17.8)	18.74 (11.9)	18.22 (15.7)	***	***	*
Change in unemployment rates 2013/2020	–4.22 (3.9)	–6.44 (3.5)	–5.40 (3.6)	–2.57 (3.4)		***	***
Change in unemployment rates 2013/2019	–4.61 (3.7)	–6.49 (3.5)	–5.45 (4.0)	–3.26 (3.2)		***	**
Change in employment rates 2013/2020	2.11 (2.9)	3.58 (2.8)	2.19 (3.7)	1.26 (2.3)	*	***	
Change in employment rates 2013/2019	2.77 (2.6)	3.87 (3.0)	2.85 (3.5)	2.13 (1.6)		***	
Number of observations							
Change in unemployment	239	70	44	125			
Change in employment	240	70	44	126			
All other Variables	281	72	58	151			

Source: ARDECO, EUROSTAT, WIFO-calculations. – The column labelled (2)=(1) reports results of a t-test for equivalent means of less developed and transition regions, the column labelled (3)=(1) for equivalence of means of less developed and more developed regions, and the column (2)=(3) for equal means of transition and more developed regions. – ***, (**), [*]: signify statistical difference in the respective indicator (based on a 2-sided t-test) at the 1%, (5%), [10%] level respectively, values in brackets are standard errors.

This statistically significant faster GDP growth among less developed regions holds across all other GDP growth indicators, irrespective of whether we measure this growth for the period 2013 to 2020 (and thus include the first year of the COVID-19 crisis) or the period 2013 to 2019 (excluding the first year of the pandemic). Furthermore, because of the deep economic decline in 2020, all GDP growth rates are higher for the period 2013 to 2019 than for the period 2013 to 2020. The only instance where regions shrank for the period 2013 to 2020 is with respect to real GDP.

Finally, unemployment rates declined - by 4.2 percentage points (pp) over the period 2013-2020 and by 4.6 pp over the period 2013–2019 - while employment rates increased slightly, by 0.2 pp in 2013-2020 and 0.3 pp in 2013-2019. However, for these indicators, there is less evidence of a more favorable development in less developed regions. For unemployment rates, more developed regions differ statistically significantly from less developed regions, with the latter showing a faster reduction. For employment rates, the differences between less developed and transition regions are marginally statistically significant, with less developed regions again performing better than the other two groups.

5. Pretests

As noted in the discussion of Section 3, for the RDD results to be valid, three central and partially testable conditions must be met. First, regional units must not be able to precisely manipulate the forcing variable. While this cannot be directly tested, a “bunching” (an accumulation) of regions just below or above the cutoff could indicate that there is a problem.

Second, in the instance of a fuzzy RDD, the instrument (the cutoff levels) must be relevant for treatment intensity (funds received). This assumption can be directly tested by examining the statistical significance of the instrument (i.e., the dummy variable for the cutoff level) in Equation (3).

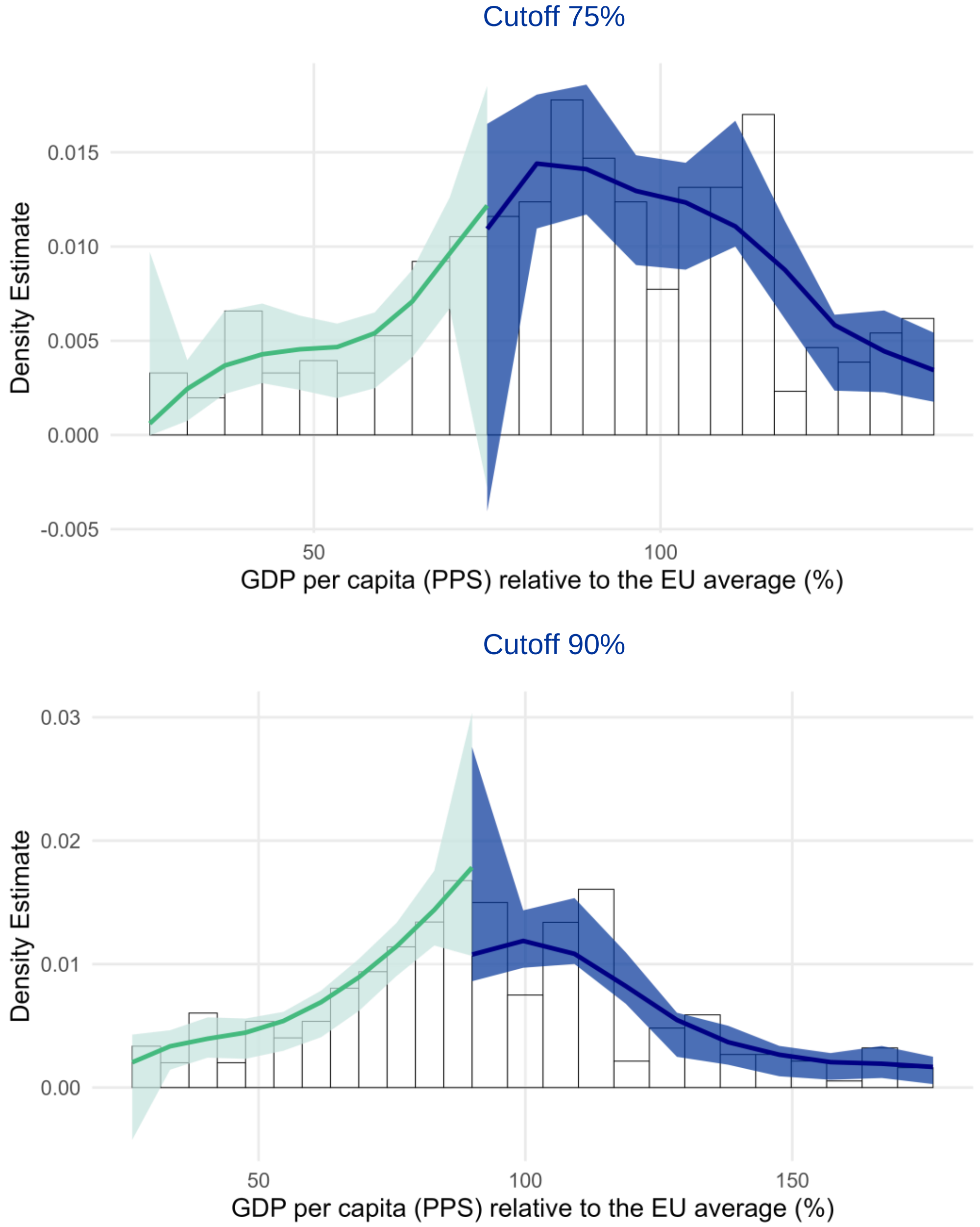
Third, there should be no discontinuities in other variables at the same cutoff levels of GDP/capita that affect the outcome. This can be investigated using placebo estimations (see, for example, Cunningham, 2021, Chapter 6).

Before estimating the RDD in full, we conducted a battery of pre-tests to assess the extent to which these assumptions hold.

5.1. Manipulation tests

The first of these tests addresses the issue of the regions’ control over their treatment status. While such a manipulation may seem unlikely, it could occur if regions foresaw that funding conditions for regional policy would be substantially more generous for regions with a GDP per capita below 75% (respectively 90%) of the EU average than above this threshold. This would create incentives to artificially reduce GDP per capita prior to the implementation of the policy, particularly in regions close to the cutoff. This might be achieved either through conservative estimation of GDP or by rezoning of NUTS-2 regions to ensure that at least the poorer parts of these regions are eligible for more generous funding. As a result of such a manipulation, one would observe a substantially larger share of regions just below– compared to just above – the 75% or 90% cutoff.

Figure 2 – Test for manipulation of the running variable



Source: Eurostat; WIFO-calculations.

The bunching test by Cattaneo, Jansson and Ma (2020) uses this logic to test whether, based on the total distribution, the number of regions located at one side of the cutoff differs substantially from what could be expected if there was no cutoff at all. The result of this test is shown in Figure 3. This shows the results for the 75% cutoff in the top panel and the results for the 90% cutoff in the bottom panel. In these diagrams, the bars represent the number of regions at each tick of the running variable, (i.e., their 2007-2009 average GDP per capita relative to the cutoff), the line is a fitted value showing the expected number at the respective tick and the shaded area is the 95%-confidence interval for this fitted value. Regions on the left of the respective cutoff are marked in red, and those to the right in blue.

In both instances, the confidence intervals at the left and the right of the cutoff show a large overlap and the test statistic developed by Cattaneo, Jansson and Ma (2020) suggests that the p-value of the null hypothesis of equal proportions of regions on both sides of the cutoff is 0.83 in the case of the 75% cutoff and 0.74 at the 90% cutoff. Thus, the null hypothesis of no bunching cannot be rejected at conventional significance levels.

5.2. Instrument validity

To test for the validity of the cutoff as an instrument for the treatment intensity, we generate two indicators of treatment intensity. The first measures regions' total received EU payments relative to their population in 2013, while the second measures EU payments received relative to their nominal GDP in 2013. To analyze instrument relevance, we inspect the results of the first-stage regression (Equation (3)) for three specifications, which are described below.

The first specification includes all observations of both less developed and transition regions (respectively transition and more developed regions), i.e., a bandwidth that ranges from 0% to 90% of initial relative GDP for the 75% cutoff and from 75% to the maximum for the 90% cutoff. We use an equal weighting scheme (i.e., a "uniform kernel") to all observations. This specification is the least flexible and is equivalent to an OLS regression that allows for different slope parameters of the running variable on either side of the cutoff, as well as an interaction term between an indicator variable for regions with initial GDP below the cutoff and the running variable. In the tables below, we refer to this specification as the *linear all* model, to highlight that we are using a linear functional form and include all observations.

The second specification is identical to the first model in terms of bandwidth and weighting (i.e., it uses all observations and a uniform kernel) but allows for a quadratic relationship between funding intensity and the running variable. This is equivalent to a simple OLS regression that allows for a linear and a squared term of the running variable (with different parameters on each side of the cutoff), as well as the respective interaction terms. This is referred to as the *quadratic all* model in the tables below.

The third model is again based on a linear relationship between the running variable and the funding intensity but uses an optimal bandwidth estimator that minimizes the mean squared error as in Calonico, Cattaneo, and Titiunik (2014) and gives a higher weight to observations closer to the cutoff according to a triangular kernel weighting scheme. This is the most demanding specification in terms of data requirements but also the most flexible. It is also the specification closest to the ones advised for by Cattaneo, Idrobo, and Titiunik (2019). We refer to this specification as the *optimal bandwidth* specification in the tables.

Table 3 displays the coefficients of the interaction term between the running variable and the dummy for regions located to the left of the cutoff. If this coefficient is significantly different from zero, this indicates that the instrument can predict funding in a statistically meaningful way. If this coefficient is statistically insignificant, it means that second stage results are based on a weak instrument and must be interpreted with great care. The number in parentheses below this coefficient is the (nearest neighbor heteroscedasticity robust) standard error of the estimate, which serves as a basis for the t-test on the coefficient. The significance of this t-test is indicated by one asterisk if the test is significant at the 10% level, by two asterisks if it is significant at the 5% level and three asterisks if it is significant at the 1% level.

The results suggest low instrument relevance. Coefficients are statistically insignificant across all specifications at the 90% cutoff and in all specifications except the "linear all" model at the 75% cutoff. This implies that, unless one accepts the strong and (relative to the literature) unconventional assumptions of the "linear all" model, there is no credible basis to identify causal effects, rendering the results inconclusive. In summary, under more flexible specifications, we cannot reject the null hypothesis of no difference in cohesion funding between regions immediately above and below the 75% and 90% policy thresholds.

Table 3: First stage regressions of Fuzzy RDD design

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	Linear all	Quadratic all	Optimal bandwidth + triangular kern.
	75%			90%		
Expenditure per capita	1.058*** (0.347)	0.691 (0.555)	0.301 (0.932)	0.060 (0.144)	0.096 (0.260)	0.094 (0.324)
Funds in % of GDP	6.744*** (2.419)	4.305 (3.869)	4.764 (6.461)	0.604 (1.005)	0.760 (1.699)	0.176 (1.853)
	Number of observations					
Left[1])	72	72	9	58	58	30 | 31
Right	58	58	12	126	126	26 | 30

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations. – The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (2). − Linear all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – optimal Bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting − *** (**) [*] – signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors. −[1]) Effective observation to the left and the right of the respective cutoff.

This finding contrasts to prior evaluations using regression discontinuity designs to assess multiple Cohesion Fund periods (e.g., Becker et al., 2010, 2012; Pellegrini et al., 2013; Bachtrögler, 2016; Ferrara et al., 2017; Percoco, 2017; Becker et al., 2018; Cerqua & Pellegrini, 2022; Lang et al., 2023), which did not include the 2014-2020 period. One potential explanation for this divergence is the limited sample size available for analysis. Even when using all observations - whether under a linear or squared specification - only 130 observations are available at the 75% cutoff and 184 observations at the 90% cutoff. When applying optimal bandwidth estimators, these numbers drop further to just 21 and 56 effective observations, respectively. [11])

Another plausible explanation lies in institutional and contextual changes during the period considered. The introduction of transition regions in the 2014–2020 programming period created an intermediate category with distinct funding access, which likely reduced the sharpness of treatment intensity declines at the 75% cutoff. Furthermore, recent evidence suggests that less developed regions grew more affluent while transition regions experienced relative declines prior to this funding period (European Commission, 2023). These dynamics may have diluted the funding disparities between less developed and transition regions compared to earlier periods. Finally, also the details of the rules governing fund allocation differed to earlier funding periods. This applies to a potentially changed importance of other factors influencing funds distribution (e.g., unemployment, youth unemployment and educational attainment level) according to the so called “Berlin formula”. It, however, also applies to the changed expenditure cap of 2.5% of national GDP in the 2014 to 2020 period, which may have “diluted” the sharpness of eligibility thresholds in cohesion policy (see European Parliament and Council 2013, pp 186 -190 for details).

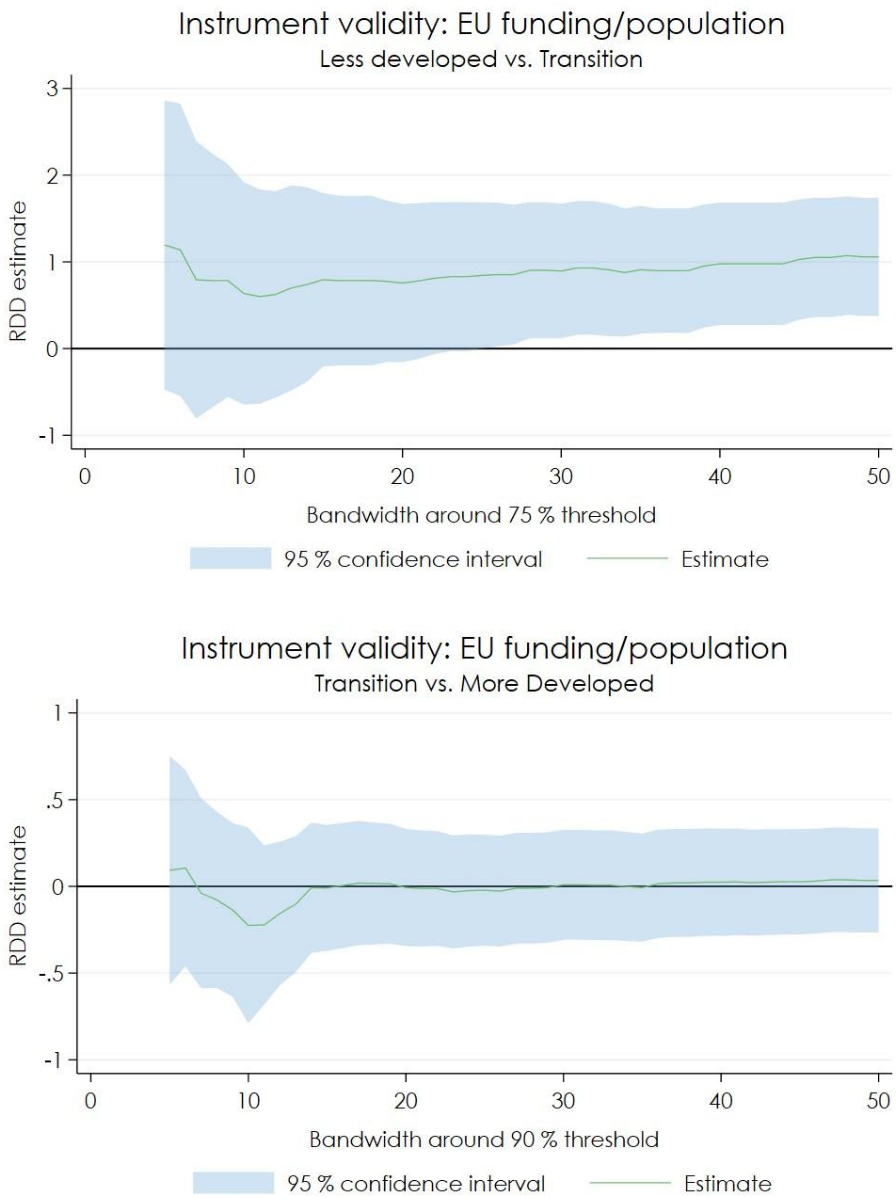
Ultimately it remains unclear whether the null finding is attributable to insufficient statistical power or a genuine lack of substantial differences in funding intensities. Given the limited sample size and overlapping distributions of funding intensities near the cutoffs, it can, however, be concluded that differences in conditional mean funding sums are too small to achieve statistical significance.

Since this result is detrimental to the aim of our paper, additional robustness checks were undertaken to see whether this insignificance of the instrument can

([11]) Interestingly, despite the general findings of a mild positive effect of cohesion policy in many RDD-studies (see Ehrlich and Overmann, 2020 for an overview) a recent study by Albanese et al. (2024) that focuses exclusively on the period 2007 to 2013 also finds an almost null effect of cohesion policy. This too may be related to the falling power of the method with a reduced number of observations.

be avoided by using other definitions of the cutoff variable and/or by focusing only on some funds or some purposes of the funds. These additional results pertain to (1) using individual funds to define the payments variables; (2) using an alternative cutoff measure considering only regions that were classified as less developed or transition regions (details on this measure and associated results are reported in Appendix D); and (3) focusing only on certain expenditure types. They are reported in the annex and do not differ from those reported here.

Figure 3: Simulation of tests for instrument relevance in dependence of the chosen bandwidth for the linear model



Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

Consequently, we were also interested how large bandwidths need to be to allow for a relevant instrument. We therefore estimated the coefficients of the linear-all specification using the complete set of possible bandwidths, both at the 75% and 90% cutoff. The line in Figure 4 plots the evolution of the coefficient across these bandwidths, and the shaded areas in that figure show the associated 5% confidence interval. As can be seen from this graph for the 90% cutoff, there is no bandwidth one could choose to allow for a statistically significant instrument. In the case of the 75% cutoff, by contrast, the instrument turns statistically significant when using a bandwidth of +/– 25 percentage points from the cutoff. This is quite far from the suggested data-driven optimal bandwidth of +/– 3.6 percentage points.

In sum this means that a statistically significant variation in treatment intensity at the cutoffs can only be found when we include less relevant information (observations further from the cutoff) and restrict the functional form to be linear.

5.3. Structural break in other causal variables

Finally in a last sequence of pretests we also checked for the presence of structural breaks in variables that may be considered relevant for regional GDP and employment growth and unemployment in the light of the pertinent literature on regional development (see e.g., Cuaresma, 2012). These variables are the starting level of real and nominal GDP per capita, GDP per capita at PPS as well as of employment and unemployment rates in 2013, as these variables have been shown to influence outcomes in a long list of publications of the convergence literature. In addition, we also checked for breaks at the cutoff of:

- Sector shares of agriculture, manufacturing, and services in GVA and employment in 2013, since overall growth rate differences among regions could be related to different underlying sector trends.
- Population shares by highest completed education, where we coded persons, whose highest completed education is ISCED[12])2 or lower as “less educated”, ISCED levels 3 and 4 as “middle educated” and ISCED level 5 or higher as “highly educated”, because a highly educated population has been shown to be one of the variables most robustly related to regional growth.
- The age structure of the population (share of population below 15, share of working age population 15 to 64, share of population aged 65 or older).

Again, for each of these variables we ran the three models already used in the previous analysis. Table 4 shows the results. For each of the models we can reject the null of no break at the cutoff for some variables. For the 75 % cutoff this applies to the real and nominal GDP in the “linear all” model, to the share of agricultural and manufacturing employment and GVA and GDP per capita at PPS

(12) ISCED is the international standard classification of educational degrees that ensures comparability of educational data across countries.

in the "quadratic all" model and to the agricultural and manufacturing GVA shares and GDP per capita at PPS in the "optimal bandwidth model". At the 90% cutoff this applies the manufacturing employment and GVA, the employment and employment rate as well as the share of young population in all specifications.

Table 4: Placebo tests for breaks at the cutoff for different variables

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	Linear all	Quadratic all	Optimal bandwidth + triangular kern.
	75%			90%		
	2013 employment shares of					
agriculture	0.0121 (0.0294)	0.0864* (0.0486)	0.0867 (0.0711)	0.0104 (0.0187)	–0.0051 (0.0270)	–0.0352 (0.0344)
production	0.0032 (0.0299)	–0.0965** (0.0450)	–0.1245** (0.0562)	–0.0741*** (0.0168)	–0.0177 (0.0255)	–0.0296 (0.0359)
services	–0.0005 (0.0050)	–0.0080 (0.0107)	–0.0234** (0.0117)	0.0098 (0.0102)	0.0008 (0.0083)	–0.0017 (0.0082)
	2013 GVA shares					
agriculture	0.0004 (0.0075)	0.0178* (0.0105)	0.0229* (0.0138)	0.0005 (0.0072)	–0.0058 (0.0105)	–0.0040 (0.0093)
production	–0.0434 (0.0397)	–0.1727** (0.0678)	–0.2072** (0.0861)	–0.0969*** (0.0232)	0.0009 (0.0336)	–0.0164 (0.0416)
services	–0.0028 (0.0051)	–0.0151 (0.0093)	–0.0131 (0.0117)	0.0054 (0.0037)	0.0017 (0.0050)	0.0062 (0.0055)
	2013 population shares of					
middle educ.	–0.0319 (0.0570)	–0.1768** (0.0790)	–0.1258 (0.0936)	–0.0630** (0.0320)	–0.0174 (0.0536)	–0.0479 (0.0711)
less educated	0.0394 (0.0634)	0.2136** (0.0886)	0.1387 (0.1078)	0.0447 (0.0362)	–0.0138 (0.0600)	–0.0231 (0.0688)
highly educated	–0.0075 (0.0212)	–0.0368 (0.0303)	–0.0111 (0.0369)	0.0183 (0.0186)	0.0312 (0.0228)	0.0729* (0.0442)
	2013 population shares of					
young	0.0071 (0.0084)	0.0089 (0.0113)	–0.0037 (0.0106)	0.0151** (0.0061)	0.0099 (0.0103)	0.0052 (0.0172)
working age	0.0055 (0.0083)	–0.0174 (0.0129)	–0.0167 (0.0182)	–0.0067 (0.0072)	–0.0045 (0.0124)	–0.0004 (0.0148)
elder	–0.0126 (0.0115)	0.0085 (0.0155)	0.0158 (0.0186)	–0.0084 (0.0098)	–0.0054 (0.0161)	–0.0052 (0.0188)
	GDP per capita (levels, 2013)					
at PPS	–0.0011 (0.0007)	–0.0035*** (0.0006)	–0.0034*** (0.0006)	–0.0001 (0.0033)	0.0007 (0.0016)	–0.0002 (0.0015)
nominal	–0.0038*** (0.0014)	–0.0031 (0.0021)	–0.0039 (0.0032)	–0.0004 (0.0037)	–0.0007 (0.0020)	–0.0006 (0.0022)
constant prices	–0.0047*** (0.0018)	–0.0043 (0.0030)	–0.0055 (0.0043)	0.0011 (0.0048)	–0.0004 (0.0026)	–0.0014 (0.0033)
	Employment & unemployment rate (levels, 2013)					
Unemployment	0.0428 (0.0400)	0.0679 (0.0655)	0.0355 (0.0801)	0.0540* (0.0311)	0.0527 (0.0530)	0.0346 (0.0756)
Employment	–0.0265 (0.0294)	–0.0586 (0.0524)	–0.0055 (0.0742)	–0.0527** (0.0212)	–0.0282 (0.0332)	0.0125 (0.0516)

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). – Linear all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – optimal Bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting – *** (**) [*] – signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

In sum, the results of this sequence of placebo tests put up several warning posts for a causal interpretation of results of an RDD, as it cannot be ruled out that any impact of EU funding found is related to a jump of other influential variables at the cutoff rather than the EU-funding.

6. Estimations Results

6.1. Sharp RDD: the intention-to-treat effect

Given the low relevance of the instrument in the fuzzy regression discontinuity design, one option may be to focus on the "intention-to-treat" effect rather than the treatment effect. Methodologically, this implies moving from a fuzzy RDD design to a sharp RDD approach (or equivalently, to focus on the reduced form of the fuzzy RDD approach). To explore this possibility, Table 5 and 6 report the results of estimating Equation (2) using the same three specifications already shown above.

Table 5: Intention-to-treat effect of EU regional policies at the 75% cutoff (Sharp RDD)

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	N
Growth of GDP per capita at PPS 2013/2020	1.322 (4.524)	–0.147 (8.881)	1.406 (13.450)	130
Growth of GDP per capita at PPS 2013/2019	2.578 (3.902)	2.911 (7.320)	5.112 (10.250)	130
Growth of real GDP per capita 2013/2020	6.207 (4.102)	–0.901 (7.906)	5.338 (11.720)	130
Growth of real GDP per capita 2013/2019	6.456* (3.758)	0.627 (6.929)	6.752 (9.844)	130
Growth of nominal GDP per capita 2013/2020	–0.148 (5.861)	–2.783 (11.050)	–1.294 (15.540)	130
Growth of nominal GDP per capita 2013/2019	1.226 (5.270)	–1.574 (9.618)	1.273 (13.200)	130
Change in unemployment rates 2013/2020	–2.193 (1.521)	–0.375 (2.317)	–1.873 (2.712)	114
Change in unemployment rates 2013/2019	–1.998 (1.463)	–0.860 (1.826)	–2.689 (1.732)	114
Change in employment rates 2013/2020	0.000699 (0.001)	0.00209 (0.002)	0.00199 (0.002)	114

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	N
Change in employment rates 2013/2019	0.000457 (0.001)	0.00211 (0.001)	0.00216* (0.001)	114

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). Linear, all = linear functional form, bandwidth of 0-90. – Uniform weighting, quadratic all = uniform weighting, quadratic functional form, bandwidth of 0-90, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. − *** (**), [*] – signify statistical significance at the 1%, (5%), [10%] level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

Table 6: Intention-to-treat effect of EU regional policies at the 90% cutoff (Sharp RDD)

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	N
Growth of GDP per capita at PPS 2013/2020	0.703 (2.961)	2.138 (4.622)	4.068 (4.992)	209
Growth of GDP per capita at PPS 2013/2019	2.635 (2.146)	2.565 (3.017)	3.858* (2.199)	209
Growth of real GDP per capita 2013/2020	1.018 (2.791)	2.998 (4.154)	4.316 (4.032)	209
Growth of real GDP per capita 2013/2019	2.576 (2.193)	2.925 (3.011)	3.654* (2.148)	209
Growth of nominal GDP per capita 2013/2020	–0.244 (3.500)	1.565 (5.424)	5.096 (6.242)	209
Growth of nominal GDP per capita 2013/2019	1.411 (2.812)	1.855 (3.918)	4.139 (2.894)	209
Change in unemployment rates 2013/2020	–2.354* (1.247)	–3.011 (2.180)	–7.395 (4.892)	169
Change in unemployment rates 2013/2019	–1.937 (1.304)	–1.330 (2.303)	–3.08 (3.780)	169
Change in employment rates 2013/2020	0.000793 (0.001)	0.000415 (0.002)	–0.0000385 (0.002)	170
Change in employment rates 2013/2019	-0.000485 (0.001)	–0.000278 (0.001)	–0.000931 (0.001)	170

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). Linear, all = linear functional form, bandwidth of 75 to the maximum, uniform weighting, quadratic all = quadratic functional form, bandwidth of 0 to 75 to maximum, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. − *** (**), [*] – signify statistical significance at the 1%, (5%), [10%} level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

Both for the 75% and 90% cutoffs, the coefficients are mostly positive for GDP growth and negative for the change in unemployment rates. This indicates increased growth and reduced unemployment in regions receiving higher funding. Coefficients are, however, statistically insignificant throughout. The only exceptions are:

- real per capita GDP growth for the period 2013 to 2019 period at the 75% cutoff in the linear model using all observations where coefficients indicate a marginally statistically significant effect for regions left of the 75% cutoff. Here the coefficients indicate that regions just to the left of this cutoff experienced a 6.5 percentage point higher GDP growth than regions just right of it.

- the change in employment rates in the 2013 to 2019 period in the optimal bandwidth model at the 75% cutoff, which is also, statistically significant at the 10% level and where the coefficient indicates a 0.002 percentage point higher increase in employment rates in regions just left of the margin than to the right.

- the change in the unemployment rate in the period 2013 to 2020 at the 90% cutoff in the case of the linear model using all observations. In this case, the marginally significant effect (at the 10% level) suggests that unemployment rates reduced by 2.4 percentage points more in transition regions just to the left of the cutoff than in developed regions just to the right.

- real and nominal per capita GDP growth in the instance of the optimal bandwidth estimator at the 90% cutoff, with the (once more marginally significant) results suggesting that transition regions just let of the cutoff experienced a 3.9 percentage point respectively 3.7 percentage point) growth rate increase in GDP per capita at PPS respectively real GDP per capita relative to developed regions to the right of the cutoff.

A common denominator across these significant results is, however, that they are all only significant at the 10% level and lack robustness across specifications. This combined with the results of the pre-test suggests that great care should be taken in interpreting these results causally.

Given the lack of a break in the treatment intensity at the 75% and 90% cutoffs the absence of a significant intention to treat effect is, however, not very surprising and provides little further insight: Given that we cannot establish the validity of the central identification assumption of the RDD approach (of a significant shift in treatment intensity at the cutoff), it is also not surprising that we cannot detect a break in the outcomes left and right of the cutoffs.

6.2. Fuzzy RDD: the treatment effect

The results of the fuzzy RDD for the 75% cutoff (in Table 7) confirm the lacking robustness of the sharp RDD and suggest that we are asking too much of the data when conducting this analysis. In the results for the 75% cutoff, coefficients are almost always insignificant, and sometimes negative. The only exception is the growth of real GDP per capita in the years 2013 to 2019 in the case of the linear model using all observations at the 75% cutoff. Here, results indicate a weakly statistically significant 6.1 percentage point growth bonus for less developed regions just left of the 75% cutoff relative to the transition regions just right of the cutoff.

In addition, results at the 90% cutoff (which are shown for illustrative purposes in Table 8) turn virtually uninterpretable, as coefficients, due to the lacking instrument validity become very large and volatile across specifications, reaching levels that cannot be considered credible from an economic point of view. It must be borne in mind, however, that these results should under no circumstances be interpreted causally.

In sum we therefore conclude that due to the lack of instrument validity the fuzzy RDD approach to identification, while attractive from a theoretical perspective, does not provide results that allow conclusions to be drawn about the causal impact of regional policy on regional development.[13])

Table 7: Treatment effect of EU regional policies at the 75% cutoff (Fuzzy RDD)

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	N
Growth of GDP per capita at PPS 2013/2020	1.25 (4.273)	−0.213 (12.860)	−2.179 (20.820)	130
Growth of GDP per capita at PPS 2013/2019	2.438 (3.583)	4.210 (10.650)	3.39 (16.920)	130
Growth of real GDP per capita 2013/2020	5.869 (4.130)	−1.303 (11.560)	4.626 (19.130)	130
Growth of real GDP per capita 2013/2019	6.105* (3.658)	0.907 (9.986)	7.555 (16.780)	130
Growth of nominal GDP per capita 2013/2020	−0.14 (5.546)	−4.025 (16.650)	−10.280 (32.490)	130
Growth of nominal GDP per capita 2013/2019	1.159 (4.914)	−2.276 (14.290)	−3.825 (23.880)	130
Change in unemployment rates 2013/2020	−2.590 (1.809)	−0.967 (5.923)	2.912 (7.089)	114
Change in unemployment rates 2013/2019	−2.360 (1.702)	−2.221 (5.079)	−4.499 (5.849)	114
Change in employment rates 2013/2020	0.00083 (0.001)	0.00539 (0.007)	−0.0019 (0.005)	114
Change in employment rates 2013/2019	0.00054 (0.001)	0.00545 (0.007)	−0.0024 (0.005)	114

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (3). Linear, all = linear functional form, bandwidth of 0-75, uniform weighting, quadratic all = quadratic functional form, bandwidth of 0-75%, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. *** (**), [*] –

([13]) We also estimated a fuzzy RDD using EU-expenditures as a measure for treatment intensity. This led to no additional insights. The results were therefore relegated to Appendix B of the current report.

signify statistical significance at the 1%, (5%), [10%} level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

As already pointed out above the central issue leading to this finding is the lacking instrument relevance. This in turn may be due to the limited sample size available for analysis as well as the institutional and contextual changes during the period considered. Here in particular:

- The introduction of transition regions in the 2014–2020 programming period
- The changed importance of other factors influencing funds distribution (e.g., unemployment, youth unemployment and educational attainment level) as well as
- the changed expenditure cap of 2.5% of national GDP in the 2014 to 2020 period,

may have contributed to “diluting” the sharpness of eligibility thresholds in cohesion policy.

Table 8: Treatment effect of EU regional policies at the 90% cutoff (Fuzzy RDD)

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	N
Growth of GDP per capita at PPS 2013/2020	20.51 (130.400)	118.5 (1872.300)	99.66 (846.700)	209
Growth of GDP per capita at PPS 2013/2019	76.90 (330.200)	142.20 (2128.300)	78.26 (493.800)	209
Growth of real GDP per capita 2013/2020	29.71 (151.600)	166.1 (2556.100)	−1165.3 (93192.300)	209
Growth of real GDP per capita 2013/2019	75.19 (324.800)	162.1 (2437.900)	172.3 (2608.200)	209
Growth of nominal GDP per capita 2013/2020	−7.127 (106.100)	86.75 (1401.300)	−1499.4 (130781.400)	209
Growth of nominal GDP per capita 2013/2019	41.18 (186.900)	102.8 (1560.200)	−408.8 (11489.900)	209
Change in unemployment rates 2013/2020	−29.12 (56.520)	−21.46 (43.710)	403.6 (16044.700)	169
Change in unemployment rates 2013/2019	−23.96 (44.170)	−9.481 (16.670)	−28.28 (136.500)	169
Change in employment rates 2013/2020	0.01 (0.024)	0.00287 (0.009)	0.000533 (0.035)	170
Change in employment rates 2013/2019	0.00614 (0.016)	−0.00192 (0.012)	0.0129 (0.069)	170

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). Linear, all = linear functional form, bandwidth of 75 to maximum, uniform weighting, quadratic all = quadratic functional form, bandwidth of 75% to maximum, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. *** (**), [*] – signify statistical significance at the 1%, (5%), [10%} level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

7. Robustness Checks

We also conducted various robustness tests and additional analyses for both the sharp and fuzzy RDD approach. These included:

- An analysis of the impact of potential outliers on results: This included omitting observation from the UK as on account of potential Brexit effects after the referendum in 2016, the exclusion of French overseas territories because they may have been exposed to rather macro-regional developments during the analysis period than the regions on the European continent, and focusing only on regions in member states that were already members of the EU before 2004.[14])
- Considering sample splits by average educational attainment. Here we separate regions which had an above and below average share of less educated residents in 2013, as Becker et al. (2012) indicate that treatment effects may vary with the average educational attainment of a region on account of this potentially having an impact on a region’s absorptive capacity.

As pretests indicate that the instruments are also invalid for these robustness checks and results lead to only few additional insights, we only report the results for the intention to treat (i.e., uninstrumented) effects for these additional robustness checks (see Table C1 to C4 in the Appendix). Thus, in cases where we drop the French overseas territories from the observations, we once more find a weakly significant parameter on real GDP growth in the period 2013 to 2020 for regions located at the 75% cutoff in the linear model using all observations, and for the change in the employment rate in the other models. At the 90% cutoff, changes in unemployment rates are weakly significantly lower for regions below the cutoff in the linear model using all observations and real GDP per capita growth is weakly significantly higher in the optimal bandwidth model. Excluding UK regions, by contrast, removes all significant effects except for a counterintuitive decrease in the employment rate between 2013 and 2019 at the 75% cutoff in the optimal bandwidth model and an equally counterintuitive increase in the unemployment rate between 2013 and 2020 at the 90% cutoff in the linear model using all observations. The same also applies to focusing only on regions of member states that joined European Union before 2004. Here only a significant reduction of unemployment rates at the 75% and 90% cutoff and on GDP per capita at PPS in the 2013 to 2019 period is found. This however only applies to the linear model using all observations.

Finally, when splitting the sample into a set of regions that had an above or below average share of residents educated at ISCED levels above 2, we find a slightly larger number of significant effects in regions with a large share of less educated

(14) Focusing on member states that joined after 2004 is precluded by the fact that the largest part of the NUTS-2 regions are less developed regions, which results in a very low number of untreated regions.

residents. In these models, however, the number of observations is too small to allow the estimation of an optimal bandwidth model and the effects are again not robust across the remaining specifications.

This paper presents a quantitative evaluation of Cohesion Funds in the 2014 - 2020 period based on an RDD design. The results highlight the challenges and limitations of evaluating the impact of EU Cohesion Policy interventions during the 2014 - 2020 programming period using regression discontinuity design (RDD). While some analyses suggest a weakly significant positive correlation between real GDP growth and labor market outcomes, these findings are not robust across specifications. Moreover, pretests assessing the assumptions required for causal interpretation reveal critical shortcomings, undermining the reliability of RDD-based estimates in this context.

- Fuzzy RDD results show statistically significant jumps in treatment intensity only under restrictive assumptions, such as linear functional forms and uniform weighting schemes. However, these effects fail to hold under more flexible specifications or bandwidth choices aligned with best practices.
- In addition, sharp RDD analysis indicates discontinuities in key covariates, such as initial GDP levels and sectoral structures, at the 75% and 90% thresholds. These discontinuities raise concerns about whether observed effects stem from policy interventions or confounding regional characteristics.

In particular, the lacking statistical significance of the discontinuity in treatment intensity near the 75% and 90% thresholds suggests that those results that show a positive correlation between regional development and regional policy cannot be interpreted causally.

The lack of statistically significant jumps in treatment intensity except under very restrictive assumptions, diverges from the findings of previous evaluations based on the RDD methodology that have used multiple structural funds periods. This discrepancy may stem from several factors: a lower number of observations due to the focus on a single-period evaluations, a shorter post-treatment observation period (necessary to avoid COVID-19-induced effects), and a reduced "sharpness" of policy thresholds during the 2014 - 2020 period, due to institutional changes cohesion policies as well as to different starting conditions in the 2014 - 2020 period. In this respect the introduction of transition regions in the policy design and reduced economic disparities in funding between less developed regions (that grew more affluent prior to the funding period), and transition regions (that tended to fall behind), as well the potentially changed importance of other factors influencing funds distribution as well as the changed expenditure cap of 2.5% of national GDP in the 2014 to 2020 period may all have worked to “dilute” the sharpness of eligibility thresholds in cohesion policy.

Future evaluations of Cohesion Policy will therefore have to carefully scrutinize the validity of identification assumptions used to identify RDDs, particularly as eligibility criteria evolve and include an increasing number of objectives. In addition, expanding analyses to include multiple programming periods and/or a larger number of regions (e.g., by using NUTS 3 regions) as well as longer post-treatment horizons could enhance statistical power and reliability of such evaluations.

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Appendices

Appendix A: First-stage regressions for alternative Funds, Expenditure types and using different treatment definitions.

Table A 1: First stage regressions for alternative Funds (using different treatment intensity measures)

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	Linear all	Quadratic all	Optimal bandwidth + triangular kern.
	75%			90%		
Cohesion Funds exp./capita	0.194** (0.079)	–0.061 (0.124)	–0.042 (0.201)	–0.006 (0.041)	0.052 (0.056)	–0.006 (0.035)
Cohesion Funds exp./GDP	1.126* (0.607)	–0.806 (0.951)	–0.064 (1.428)	0.041 (0.348)	0.405 (0.449)	–0.038 (0.246)
ERDF exp./capita	0.568*** (0.198)	0.355 (0.319)	0.199 (0.543)	0.056 (0.082)	0.063 (0.151)	0.094 (0.192)
ERDF exp./GDP	3.713*** (1.350)	2.110 (2.174)	2.576 (3.828)	0.363 (0.506)	0.462 (0.927)	0.241 (1.062)
Youth empl. Ini. Expend./capita	0.014** (0.007)	0.019* (0.010)	0.024* (0.013)	0.007 (0.006)	0.003 (0.010)	0.010 (0.014)
Youth empl. Ini. GDP Expend./GDP	0.100** (0.042)	0.155** (0.061)	0.226*** (0.077)	0.049 (0.031)	0.016 (0.052)	0.036 (0.072)
ESF/capita	0.230*** (0.075)	0.219* (0.119)	0.270 (0.180)	0.007 (0.022)	0.013 (0.036)	0.011 (0.050)
ESF/GDP	1.562*** (0.515)	1.527* (0.818)	2.285* (1.219)	0.094 (0.152)	0.105 (0.247)	–0.033 (0.320)
REACT/capita	0.051 (0.062)	0.158* (0.083)	0.046 (0.067)	–0.003 (0.028)	–0.036 (0.056)	0.011 (0.084)
REACT/GDP	0.243 (0.382)	1.319** (0.523)	0.441 (0.504)	0.056 (0.152)	–0.228 (0.313)	0.043 (0.429)
	Effective observations					
Left[1])	72	72	9	58	58	30
Right	58	58	12	126	126	26

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

Table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (2). Linear, all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. *** (**), [*] – signify statistical significance at the 1%, (5%), {10%} level, Values in brackets are (nearest neighbor) heteroscedasticity robust standard errors. – [1]) Effective observation to the left and the right of the respective cutoff.

Table A 2: First stage regressions for alternative Expenditure types (using different treatment intensity measures)

	Linear all	Quadratic all	Optimal bandwidth + triangular kern.	Linear all	Quadratic all	Optimal bandwidth + triangular kern.
	75%			90%		
AIS/capita	0.140* (0.078)	0.250** (0.125)	0.299** (0.134)	–0.021 (0.020)	–0.054 (0.035)	–0.088 (0.062)
AIS/GDP	0.008 (0.005)	0.0206** (0.008)	0.0245*** (0.008)	–0.001 (0.001)	–0.003 (0.002)	–0.006 (0.004)
Human capital/capita	0.247*** (0.095)	0.294** (0.146)	0.244 (0.187)	0.011 (0.039)	–0.018 (0.074)	–0.024 (0.087)
Human capital/GDP	0.0168*** (0.006)	0.0211** (0.010)	0.021 (0.013)	0.002 (0.002)	–0.001 (0.004)	–0.002 (0.005)
Infrastructure/ capita	0.260* (0.139)	0.169 (0.199)	–0.136 (0.377)	0.045 (0.056)	0.055 (0.117)	0.093 (0.120)
Infrastructure/GDP	0.0163* (0.010)	0.012 (0.014)	–0.000 (0.026)	0.002 (0.004)	0.003 (0.007)	0.004 (0.007)
RTD/ capita	0.162*** (0.049)	0.031 (0.082)	0.089 (0.129)	0.020 (0.026)	0.043 (0.037)	0.065 (0.062)
RTD/GDP	0.0120*** (0.004)	–0.000 (0.006)	0.007 (0.009)	0.002 (0.002)	0.004 (0.002)	0.002 (0.002)
Techn. Ass./capita	0.0339**** (0.009)	0.015 (0.014)	0.014 (0.022)	–0.001 (0.004)	0.005 (0.005)	–0.001 (0.006)
Techn. Ass./GDP	0.00226**** (0.001)	0.001 (0.001)	0.001 (0.002)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)
Transport/capita	0.216*** (0.070)	–0.068 (0.121)	–0.012 (0.209)	0.006 (0.035)	0.065 (0.049)	0.011 (0.031)
Transport/GDP	0.0116** (0.005)	–0.011 (0.009)	0.001 (0.015)	0.001 (0.003)	0.005 (0.004)	0.001 (0.002)
N	130	130	130	209	209	209

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (2). Linear, all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. *** (**), [*] – signify statistical significance at the 1%, (5%), [10%] level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors. – [1]) AIS = Aid to private sector.

Appendix B: Additional robustness checks for fuzzy RDD

Table B 1: Robustness using expenditure as a percentage of GDP as treatment intensity (Fuzzy RDD)

	Growth of						Change in			
	GDP per capita at PPS		Real GDP per capita		Nominal GDP per capita		Unemployment rate		Employment rate	
	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019
	75% cutoff									
Linear all	0.196 (0.663)	0.382 (0.548)	0.92 (0.627)	0.957* (0.549)	–0.0219 (0.871)	0.182 (0.762)	–0.383 (0.285)	–0.349 (0.258)	0.000122 (0.000)	0.0000798 (0.000)
Quadratic all	–0.0342 (2.069)	0.676 (1.641)	–0.209 (1.886)	0.146 (1.586)	–0.646 (2.775)	–0.366 (2.351)	–0.136 (0.863)	–0.313 (0.744)	0.000759 (0.001)	0.000767 (0.001)
Optimal Bandwidth + triangular kern.	0.0396 (1.860)	0.451 (1.585)	0.582 (1.668)	0.805 (1.471)	–0.568 (2.625)	–0.244 (2.278)	–0.401 (0.796)	–0.444 (0.462)	0.000549 (0.001)	0.000407 (0.001)
N	130	130	130	130	130	130	114	114	114	114
	90% cutoff									
Linear all	2.846 (16.340)	10.67 (42.780)	4.122 (18.970)	10.43 (42.140)	–0.989 (15.300)	5.714 (23.220)	–5.26 (15.210)	–4.329 (12.090)	0.00179 (0.006)	0.0011 (0.004)
Quadratic all	5.732 (31.310)	6.879 (31.330)	8.038 (40.010)	7.843 (36.180)	4.198 (25.580)	4.975 (24.130)	–3.068 (6.652)	–1.356 (2.644)	0.000415 (0.001)	–0.000278 (0.002)
Optimal Bandwidth+ triangular kern	17.06 (152.300)	–27.03 (346.000)	18.95 (166.300)	–22.35 (257.800)	–39.34 (506.800)	–22.57 (208.700)	13.21 (119.500)	1.377 (9.083)	–0.0000227 (0.002)	0.000829 (0.002)
N	209	209	209	209	209	209	169	169	170	170

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (3). Linear, all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to the maximum for the 90% cutoff, uniform weighting, quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to the maximum for the 90% cutoff, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. *** (**), [*] – signify statistical significance at the 1%, (5%), [10%} level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

Appendix C: Additional robustness checks for sharp RDD (intention-to-treat effect)

Table C 1: Intention-to-treat effect dropping French overseas territories (Sharp RDD)

	Growth of						Change in			
	GDP per capita at PPS		Real GDP per capita		Nominal GDP per capita		Unemployment rate		Employment rate	
	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019
						75% cutoff				
Linear all	0.934 (4.646)	2.537 (4.012)	6.151 (4.170)	6.752* (3.774)	–0.266 (5.987)	1.509 (5.366)	–1.5 (1.484)	–1.574 (1.432)	0.000887 (0.001)	0.000732 (0.001)
Quadratic all	–0.705 (9.019)	2.917 (7.454)	–1.667 (7.970)	0.589 (6.932)	–1.851 (11.200)	–0.205 (9.735)	–0.51 (2.284)	–1.442 (1.774)	0.00276* (0.002)	0.00282* (0.001)
Optimal Bandwidth + triangular kern.	0.151 (13.590)	4.69 (10.310)	4.695 (11.760)	7.133 (9.870)	–2.211 (15.710)	1.242 (13.340)	–1.656 (2.797)	–2.657 (1.874)	0.00252* (0.001)	0.00246* (0.001)
N	125	125	125	125	125	125	109	109	109	109
	90% cutoff									
Linear all	0.703 (2.961)	2.635 (2.146)	1.018 (2.791)	2.576 (2.193)	–0.244 (3.500)	1.411 (2.812)	–2.354* (1.247)	–1.937 (1.304)	0.000793 (0.001)	0.000485 (0.001)
Quadratic all	2.138 (4.622)	2.565 (3.017)	2.998 (4.154)	2.925 (3.011)	1.565 (5.424)	1.855 (3.918)	–3.011 (2.180)	–1.330 (2.303)	0.000415 (0.002)	–0.000278 (0.001)
Optimal Bandwidth + triangular kern.	4.068 (4.992)	3.858* (2.199)	4.316 (4.032)	3.654* (2.148)	5.096 (6.242)	4.139 (2.894)	–7.395 (4.892)	–3.080 (3.780)	–0.0000385 (0.002)	–0.000931 (0.001)
N	209	209	209	209	209	209	169	169	170	170

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). Linear, all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. *** (**), [*] – signify statistical significance at the 1%, (5%), [10%} level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

Table C 2: Intention-to-treat effect dropping UK (Sharp RDD)

	Growth of						Change in			
	GDP per capita at PPS		Real GDP per capita		Nominal GDP per capita		Unemployment rate		Employment rate	
	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019
	75% cutoff									
Linear all	–0.611 (5.696)	–1.026 (4.841)	–5.738 (5.226)	–5.613 (4.835)	1.211 (7.241)	0.43 (6.514)	2.193 (1.521)	1.998 (1.463)	–0.000699 (0.001)	–0.000457 (0.001)
Quadratic all	–0.256 (11.800)	–2.302 (9.633)	0.492 (10.620)	–0.768 (9.304)	2.779 (14.480)	2.22 (12.570)	0.375 (2.317)	0.86 (1.826)	–0.00209 (0.002)	–0.00211 (0.001)
Optimal Bandwidth + triangular kern.	–1.071 (15.830)	–3.941 (12.310)	–4.257 (13.730)	–6.071 (11.880)	1.607 (18.590)	–0.945 (16.200)	1.873 (2.712)	2.689 (1.732)	–0.00199 (0.002)	–0.00216* (0.001)
N	114	114	114	114	114	114	114	114	114	114
	90% cutoff									
Linear all	–1.219 (4.068)	–3.149 (2.833)	–1.591 (3.919)	–3.191 (3.185)	0.0797 (4.857)	–1.539 (3.916)	2.354* (1.247)	1.937 (1.304)	–0.000793 (0.001)	–0.000485 (0.001)
Quadratic all	–1.843 (6.759)	–2.146 (4.154)	–3.189 (6.062)	–2.986 (4.592)	–1.2 (8.075)	–1.515 (5.735)	3.011 (2.180)	1.330 (2.303)	–0.000415 (0.002)	0.000278 (0.001)
Optimal Bandwidth + triangular kern.	–6.625 (6.658)	–4.632 (2.867)	–6.877 (5.461)	–4.829 (3.602)	–8.046 (8.426)	–6.293 (4.107)	7.395 (4.892)	3.080 (3.780)	0.0000385 (0.002)	0.000931 (0.001)
N	170	170	170	170	170	170	169	169	170	170

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations. – The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). Linear, all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting, optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting. *** (**), [*] – signify statistical significance at the 1%, (5%), [10%] level, Values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

Table C 3: Intention-to-treat effect focusing only on member states before 2004 (Sharp RDD)

	Growth of						Change in			
	GDP per capita at PPS		Real GDP per capita		Nominal GDP per capita		Unemployment rate		Employment rate	
	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019
	75% cutoff									
Linear all	–0.822 (4.295)	2.249 (3.531)	2.814 (3.547)	4.632 (3.304)	–3.204 (4.935)	–0.590 (4.266)	–3.667* (2.202)	3.000 (2.310)	0.00158 (0.00121)	0.00106 (0.00114)
Quadratic all	7.347 (7.748)	9.770 (6.678)	9.783 (7.833)	10.83 (7.605)	4.742 (9.067)	6.400 (8.28)	–0.465 (2.928)	–1.426 (2.557)	0.00343 (0.00224)	0.00263 (0.00201)
N	76	76	76	76	76	76	60	60	60	60
	90% cutoff									
Linear all	0.696 (2.571)	3.057* (1.793)	0.558 (2.31)	2.445 (1.758)	0.0042 (2.941)	2.089 (2.196)	–2.467* (1.358)	–2.114 (1.427)	0.00124 (0.00136)	0.000865 (0.00119)
Quadratic all	–1.595 (4.154)	0.185 (2.48)	–1.200 (3.626)	–0.031 (2.477)	–2.582 (4.702)	–1.136 (2.999)	–3.39 (2.314)	–1.416 (2.473)	0.000804 (0.00174)	0.000152 (0.00137)
N	197	197	197	197	197	197	157	157	158	158

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations. – The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). – Linear all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting – *** (**) [*] – signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors.

Table C 4: Intention-to-treat effect (sample split: high vs low educated)

	Growth of						Change in			
	GDP per capita at PPS		Real GDP per capita		Nominal GDP per capita		Unemployment rate		Employment rate	
	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019
	75% cutoff									
	high educated									
Linear all	1.032 (5.363)	1.621 (5.049)	3.718 (5.556)	3.245 (5.53)	–2.828 (6.389)	–2.742 (6.18)	–1.141 (2.175)	–0.701 (2.28)	–0.00148 (0.00128)	–0.00178 (0.00128)
Quadratic all	6.734 (10.59)	6.706 (9.346)	7.603 (11.02)	5.921 (10.5)	3.256 (11.79)	1.466 (10.86)	0.297 (3.106)	(0.768 (3.006)	0.000973 (0.00219)	0.00102 (0.00194)
Optima Bandwidth and width + triangular kern.	24.35 (29.68)	22.7 (20.88)	27.84 (30.29)	24.18 (23.91)	21.54 (31.63)	23.32 (25)	0.0382 (3.306)	2.853 (2.378)	0.000308 (0.0025)	0.000922 (0.00184)
N	73	73	73	73	73	73	67	67	67	67
	low educated									
Linear all	4.541 (5.53)	7.303 (5.007)	7.674 (4.749	9.906* (3.91)	7.436 (7.361)	11.14* (6.25)	-2.308* (1.148)	–2.765** (0.958)	0.00344** (0.001159)	0.00379** (0.000916)
Quadratic all	0.458 (9.571)	3.326 (8.436)	–1.689 (7.745	1.113 (6.015)	4.893 (12.78)	6.497 (10.58)	1.961 (1.572)	0.938 (1.381)	0.0016 (0.001749)	0.00186 (0.0015)
N	57	57	57	57	57	57	47	47	47	47

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

High educated = regions with above average share of population with education above ISCED 2, Low educated = regions with below average share with education above ISCED 2. Table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). – Linear all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting – *** (**) [*] – signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors. – [1] Effective observation to the left and the right of the respective cutoff

Table C 5 continued: Intention-to-treat effect (sample split: high vs low educated)

	Growth of						Change in			
	GDP per capita at PPS		Real GDP per capita		Nominal GDP per capita		Unemployment rate		Employment rate	
	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019	2013/2020	2013/2019
	90% cutoff									
	high educated									
Linear all	0.668 (3.431)	1.655 (2.434)	0.179 (3.136)	0.889 (2.628)	–0.428 (3.766)	0.377 (2.965)	–0.809 (1.601)	–0.651 (1.809)	0.000704 (0.00142)	0.00011 (0.0014)
Quadratic all	–5.802 (6.466)	–4.46 (4.071)	–5.736 (5.778)	–4.918 (4.549)	–7.567 (6.975)	–6.448 (5.215)	–2.273 (2.627)	–0.355 (3.201)	–0.0000368 (0.00137)	–0.00072 (0.00165)
Optimal Bandwidth + triangular kern.	6.962 (9.582)	7.318 (5.817)	4.964 (6.957)	4.534 (6.159)	11.22 (10.810)	8.828 (7.773)	–7.34 (4.694)	–7.534 (7.131)	–0.000618 (0.00151)	–0.00118 (0.00184)
N	105	105	105	105	105	105	95	95	96	96
	low educated									
Linear all	3.825 (5.627)	4.725 (4.333)	5.066 (6.43)	6.207 (5.037)	4.883 (6.302)	6.075 (4.982)	–3.201* (1.322)	–2.651** (0.947)	–0.000945 (0.00193)	–0.000333 (0.000944)
Quadratic all	8.721 (6.648)	8.234 (5.057)	10.71 (7.807)	9.851 (6.199)	9.422 (7.368)	9.031 (5.694)	–5.327* (2.529)	–3.606** (1.002)	0.000991 (0.00303)	–0.0000566 (0.00131)
N	104	104	104	104	104	104	74	74	74	74

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations.

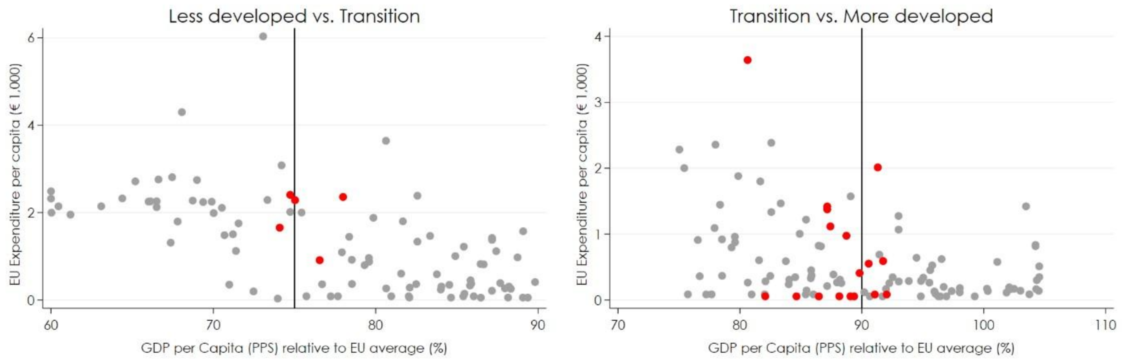
High educated = regions with above average share of population with education above ISCED 2, Low educated = regions with below average share with education above ISCED 2. Table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). – Linear all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – optimal bandwidth = linear functional form, optimal bandwidth, triangular kernel weighting – *** (**) [*] – signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors. – [1] Effective observation to the left and the right of the respective cutoff

Appendix D: Alternative definition of the treatment group indicator

Regression Discontinuity Designs use a binary treatment group indicator to identify observations that are below or, respectively, above a cutoff. In Equations (2),(3) and (4) this treatment group indicator is given by the Variable D_i which indicates whether a region is below the 75% (or 90%) cutoff value (= 1) or not (= 0). However, not all regions with an average 2007-2009 GDP per capita (in PPP) of less than 75% relative to the EU average are categorized as “less developed” regions, and not all regions with a relative GDP per capita of more than 75% are “transition regions”. Similar observations can be made at the 90% cutoff, where some regions below the cutoff are categorized as “more developed” while others above the cutoff are in the “transition” region category.

Figure D 1 highlights these cases and shows that they are generally rare (especially around the 75% cutoff). In some instances, this may be probably due to rounding errors, in others it may be because regional definitions have changed between different versions of the NUTS classification. Nevertheless, there may be concerns that this affects our results. We therefore estimated additional robustness checks using the categorization of regions into the “less developed”, “transition” and “more developed” categories in the data made available to us as treatment group indicator D_i instead of a “below 75%” (“below 90%”, respectively) indicator.

Figure D 1: Region categories vs. policy cutoffs



Source: European Commission, Eurostat, ARDECO, WIFO-calculations. – The figures only show regions within a +/–15 percentage point bandwidth around the respective cutoffs.

Table D1 replicates the results of Table 3 in the main text[15]). It shows that this alternative definition of the treatment group indicator leads to no change in instrument validity. The estimated first stage coefficients are virtually unchanged

[15]) The „linear optimal bandwidth“ model is missing because the estimation routine used to calculate optimal bandwidths does not allow regions below the cutoff that are untreated or regions above the cutoff that are treated.

and again statistically insignificant, except for the inflexible “linear all” specification at the 75% cutoff. Furthermore, the results are again sensitive regarding the bandwidth, as shown by Figure D2, which replicates Figure4 in the main text: only at relatively large bandwidths of more than +/–20 percentage points will the linear first stage estimates turn significant at the 75% cutoff, while they are statistically never significant at the 90% cutoff. Defining treatment groups by categorization and not by their relative GDP per capita does therefore not increase the relevance of the treatment group indicator, questioning its use as an instrument.

Table D 1: First stage regressions of Fuzzy RDD design, alternative treatment group indicator

	Linear all	Quadratic all	Linear all	Quadratic all
	75%		90%	
Expenditure per capita (in 1000s)	1.040*** (0.327)	0.639 (0.453)	0.143 (0.168)	0.105 (0.212)
Funds in % of GDP	6.542*** (2.321)	3.651 (3.360)	0.884 (1.118)	0.387 (1.455)
Observations				
Left[1])	72	72	58	58
Right	58	58	126	126

Source: Eurostat, DG-Regio, ARDECO, WIFO-calculations. – The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (2). − Linear all = linear functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. – quadratic all = quadratic functional form, bandwidth of 0-90 for 75% cutoff respectively 75 to maximum for the 90% cutoff, uniform weighting. *** (**) [*] – signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbor) heteroscedasticity robust standard errors. −[1]) Effective observation to the left and the right of the respective cutoff.