WIFO ■ WORKING PAPERS
720/2026

Counterfactual Impact Evaluation of Cohesion Policy 2014-2020: Impact on Enterprises

Alexander Daminger
Peter Huber
Klaus Nowotny

Counterfactual Impact Evaluation of Cohesion Policy 2014-2020: Impact on Enterprises

Alexander Daminger, Peter Huber, Klaus Nowotny

WIFO Working Papers 720/2026
February 2026

Abstract

This paper examines the impact of the European Union's Cohesion Policy 2014-2020 on enterprise dynamics at the NUTS-2 level. Using discrete eligibility thresholds at 75 and 90 percent of EU average GDP per capita, we implement sharp and fuzzy regression discontinuity designs to assess effects on enterprise births and deaths, changes in the number of and employment in enterprises and local units. The analysis draws on ARDECO, DG REGIO, and Eurostat data, and considers both the full period (2014-2020) and a pre-pandemic subsample (2014-2019). We find no robust evidence of statistically significant discontinuities in treatment intensity at the thresholds, except under restrictive model assumptions. This lack of sharp jumps in funding intensity, combined with low statistical power, prevents credible identification of causal effects on enterprise outcomes. Moreover, diagnostic tests reveal structural breaks in key regional characteristics (e.g., sectoral structure, education, initial enterprise density) at the cutoffs, violating core RDD assumptions and suggesting confounding. We argue that institutional changes – the introduction of "transition regions" category, smoothed eligibility rules, and additional allocation criteria such as unemployment – have weakened the quasi-experimental nature of GDP-based thresholds. Future evaluations should rely on multiperiod designs and alternative identification strategies.

E-Mail: alexander.daminger@wifo.ac.at, peter.huber@wifo.ac.at, klaus.nowotny@wifo.ac.at

2026/1/W/24097

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/67171803

Counterfactual Impact Evaluation of Cohesion Policy 2014-2020

Impact on Enterprises

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 2024CE16BAT059.

Abstract

This paper examines the impact of the European Union's Cohesion Policy 2014–2020 on enterprise dynamics at the NUTS-2 level. Using discrete eligibility thresholds at 75% and 90% of EU average GDP per capita, we implement sharp and fuzzy regression discontinuity designs to assess effects on enterprise births and deaths, changes in the number of and employment in enterprises and local units. The analysis draws on ARDECO, DG REGIO, and Eurostat data, and considers both the full period (2014–2020) and a prepandemic subsample (2014–2019).

We find no robust evidence of statistically significant discontinuities in treatment intensity at the thresholds, except under restrictive model assumptions. This lack of sharp jumps in funding intensity, combined with low statistical power, prevents credible identification of causal effects on enterprise outcomes. Moreover, diagnostic tests reveal structural breaks in key regional characteristics (e.g., sectoral structure, education, initial enterprise density) at the cutoffs, violating core RDD assumptions and suggesting confounding. We argue that institutional changes – the introduction of 'transition regions' category, smoothed eligibility rules, and additional allocation criteria such as unemployment – have weakened the quasi-experimental nature of GDP-based thresholds. Future evaluations should rely on multiperiod designs and alternative identification strategies.

Key Words: Regional Policy, Firm growth and demography, Evaluation

JEL-Codes: R11, O40, C21

---

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

Contents

Executive summary

This study conducts a counterfactual impact evaluation of the European Union's Cohesion Policy for the 2014–2020 programming period, focusing on its effects on enterprises and business start-ups at the NUTS-2 regional level. The Cohesion Policy, accounting for approximately one-third of the EU budget during this period, aimed to reduce regional disparities by investing in job creation, sustainable economic growth, and social inclusion, primarily through the European Regional Development Fund (ERDF), the European Social Fund (ESF), and the Cohesion Fund (CF). The policy framework was further adapted to mitigate the impacts of the COVID-19 pandemic and geopolitical shocks, notably through the CRII, REACT-EU, CARE, and Fast-CARE initiatives.

The central objective of this study is to identify the (causal) impact of Cohesion Policy interventions on key enterprise outcomes, namely, enterprise births and deaths, changes in the number of enterprises and local units, and changes in employment within enterprises and local units during the 2014–2020 programming period. The study employs a regression discontinuity design (RDD), leveraging the discrete eligibility thresholds at 75% and 90% of average EU GDP per capita, which determine the intensity of funding allocated to less developed, transition, and more developed regions.

Two variants of the RDD are implemented: the sharp RDD, estimating the intention-to-treat effect, and the fuzzy RDD, estimating the local average treatment effect using the cutoff as an instrument for treatment intensity. The analysis is based on comprehensive datasets from ARDECO, DG-Regio, and Eurostat, with outcome indicators calculated for both the full period (2014–2020) and a pre-pandemic subsample (2014–2019) to mitigate COVID-19-related confounding effects.

Contrary to prior evaluations spanning multiple programming periods, the study finds no statistically significant discontinuities in treatment intensity (measured as EU funding per capita or as a share of GDP) at the 75% and 90% GDP per capita thresholds, except under restrictive model assumptions (e.g., linear functional forms or wide bandwidths). This absence of pronounced jumps in funding intensity fundamentally limits the statistical power and identification capacity of the RDD approach for this period.

Estimation results from both sharp and fuzzy RDDs yield no consistent or robust evidence of causal effects of Cohesion Policy on enterprise outcomes. While isolated coefficients attain statistical significance in certain model specifications, these results are highly sensitive to functional form, bandwidth selection, and sample composition, and are not robust across alternative specifications or subsamples. Pretests further reveal structural breaks in key covariates (e.g., sectoral composition, education, initial enterprise numbers) at the policy cutoffs, undermining the validity of the RDD identification strategy and suggesting that observed effects could be attributable to these confounding variables.

The study concludes that, for the 2014–2020 programming period, the lack of a sharp discontinuity in funding intensity – attributable to institutional changes such as the introduction of transition regions, the smoothing of eligibility thresholds, and the inclusion of variables other than relative regional GDP (e.g., the level of (relative) unemployment) in the funding allocation mechanism – precludes reliable causal inference using RDD. Future evaluations should consider multi-period designs, longer post-treatment horizons, and alternative identification strategies to enhance robustness and reliability. As eligibility criteria and regional classifications are likely to continue to evolve in future programming periods, careful tests of the RDD assumptions will be essential for credible policy impact assessment.

1. Introduction

Under the 2014–2020 multiannual financial framework, cohesion policy accounted for about one third of the European Union (EU) budget. 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 favoured 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 (ESF), and the Cohesion Fund (CF).

These interventions 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 throughout the programming period 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 study conducts a quantitative evaluation of the impact of EU Cohesion Policy interventions in the 2014–2020 programming period on enterprises and business start-ups.

To identify the causal effects of these regional policies, we build on previous contributions (Becker et al., 2010, 2012; Ferrara et al., 2017; Pellegrini et al., 2013; Percoco, 2017) and apply a regression discontinuity design (RDD) approach. This method leverages the fact that the amount of funds available from the ERDF, ESF, and Cohesion Fund varies significantly between regions with GDP per capita at purchasing power parity (PPP) below and above 75% and 90% of the EU average. We analyse six key outcome variables: The cumulative number of enterprise births and deaths, the change in number of enterprises and local units, and the change in employment in enterprises and local units. To mitigate possible contamination of our results by the COVID-19 crisis, we focus on two distinct periods of analysis (2014 to 2020 and 2014 to 2019).

While prior RDD-based evaluations have predominantly examined multiple programming periods collectively (e.g., Bachtrögler, 2016; Becker et al., 2018; Lang et al., 2023) or focused on NUTS-3 level data (e.g., Cerqua & Pellegrini, 2022; Gagliardi & and Percoco, 2017), this study, exclusively focusses on the 2014–2020 programming period 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 in percent of 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.

We do not find consistent and reliably robust results for any of our measured outcomes. Especially when applying more flexible functional forms, more conventional forms of weighting of observations or more conventional bandwidth choices following the scientific literature and best practice recommendations for RDD analyses, results mostly turn statistically insignificant.

The next section of this interim report describes the specifics of the program. Section 3 outlines the overarching methodological approach and details its central identification assumptions. Section 4 presents the data and provides descriptive statistics. Section 5 then presents a series of pretests to test these identification assumptions, while Section 6 discusses estimation results. Section 7 reports the results for further robustness checks and extensions, while Section 8 concludes.

2. The specifics of EU cohesion 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:

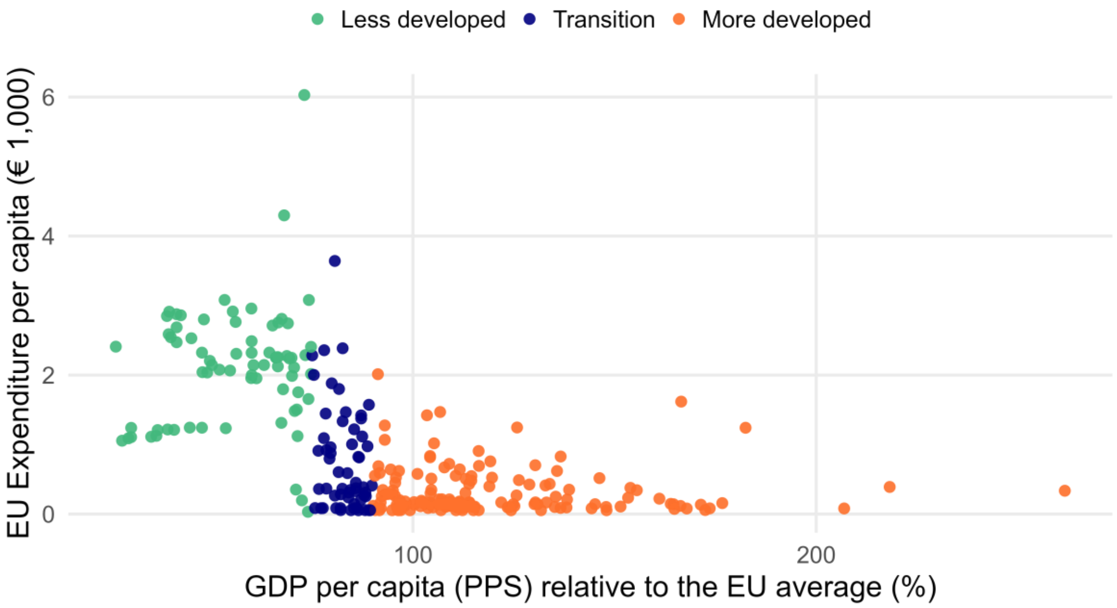
- Less developed regions whose Gross Domestic Product (GDP) per capita was less than 75% of the EU-27 average,
- Transition regions whose GDP per capita ranged between 75% and 90% of the EU-27 average, and
- More developed regions whose GDP per capita exceeded 90% of the EU-27 average.

While the largest share of the funds was directed toward less developed regions, both transition and more developed regions were also eligible for funding. In

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

addition, eligibility for the Cohesion Fund was determined at the member state: 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).

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)

Figure 1 plots EU expenditure per capita 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 ([3]). 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.

Fehler! Ungültiger Eigenverweis auf Textmarke. augments this information by providing the (population weighted) average funding per capita in total and disaggregated by fund, category, and 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 types.

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

(3) 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.

the various funds, these differences are most pronounced in the cohesion fund and in 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 as well as lower levels of existing infrastructure endowments, and therefore greater investment needs, in less developed regions ([4]).

Table 1 – EU Expenditure by fund, category, and region type

	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: DG-Regio, Eurostat; WIFO-calculations.

Regions are categorised 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”.

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; European Commission, 2016; Pellegrini et al., 2013) 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

([4]) 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.

facilitates comparability of results across intervention periods. A further advantage is that the method focuses primarily relies on cross-sectional variation in the data, and thus minimizes concerns related to repeated treatments.

One disadvantage of the RDD approach is, however, that it only allows for an identification of local average treatment effects, that is, the effects of funding for regions just below relative to regions just above the cutoff. For regions located further 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 treatment is binary) or the expected value of treatment (if treatment is continuous, as in our case) exhibits a "discontinuous jump" at the cutoff.

In an ideal statistical application, this would require many 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 72 belong to the category of “less developed”, 58 to “transitional”, and 151 to “more developed” in the 2014 to 2020 programming period ([5]).

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

In addition, while the allocation of cohesion policy funding is formally based on eligibility thresholds at 75% and 90% of the EU average GDP per capita, in practice, the actual allocation mechanism is more complex and apparently not determined solely by these cutoffs. Several factors contribute to this: (i) both regions just below and just above the threshold remain eligible for funding, albeit at different intensities; (ii) the introduction of transition regions in the 2014–2020 period created an intermediate category, further smoothing differences in funding intensity across the threshold; and (iii) regional authorities retain discretion in the uptake and implementation of available funds. Furthermore, the allocation mechanism also incorporates non-GDP factors such as the level of youth unemployment as well as capping and safety nets that "smoothen" the distribution to mitigate abrupt funding changes across funding periods and region types (European Court of Auditors, 2019). As a result, the empirical distribution of funding intensity does not display a sharp discontinuity at the cutoffs. This means

([5]) This classification results from the allocation of regions to the three categories according to their average GDP at PPS for the years 2007 to 2009 as a percentage of the EU average, the algorithm that was implemented for region categorization according to the programme legislation. However, this differs slightly from the allocation used in implementation, where 73 regions were 'less developed', 50 'transitional' and 158 'more developed'. We will return to this issue later in the report, and also provide a robustness check of our results with the implemented allocation scheme.

that, even for regions just below and just above the threshold, differences in funding can be relatively modest.

This lack of a pronounced 'jump' in treatment intensity around the threshold limits the statistical power of the RDD approach, as the core identification assumption that the probability or intensity of treatment changes abruptly at the cutoff is not fully met. Consequently, we do not observe large enough differences in funding between regions just below and just above the cutoff for the RDD to yield statistical significant results. This limitation is reflected in our empirical findings, where statistically significant discontinuities in treatment intensity at the cutoff are only observed under restrictive model assumptions or when including observations far from the threshold, which undermines the local identification strategy. This structural feature of the policy context limits the applicability of the RDD approach for the 2014–2020 period.

3.1. Sharp RDD

The Regression Discontinuity Design (RDD) leverages 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.

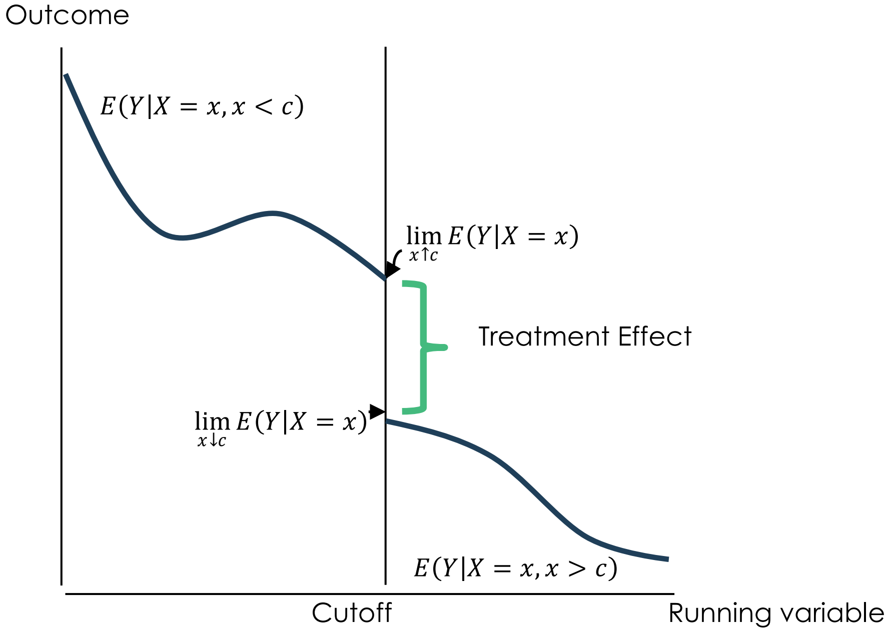
Formally, RDD relies on two key components: (i) a running (or score) variable *X*, which in our case is GDP per capita at PPS, and (ii) a cutoff value *c* (which in our case corresponds to 75% and 90% of the EU average GDP per capita at PPS). This defines the value of the running variable at which (more intense) treatment applies. The central idea is that, given these components, the expected outcome (Y) for a region that is 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 that is 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 and right of the cutoff, the local average treatment effect (LATE) of the policy can be estimated by (see Hahn et al. (2001) for a proof):

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

Fehler! Ungültiger Eigenverweis auf Textmarke. shows a graphical representation of this approach. The vertical axis measures the outcome, while the horizontal axis measures the running variable. The vertical line at the cutoff-point c represents the cutoff. Furthermore, the (cubic) functions on the left and the right of the cutoff (denoted by $E(Y|X = x, x < c)$ and $E(Y|X = x, x > c)$)

represent estimates of the expected outcomes as a function of the running variable to the left and the right 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 these two is the local average treatment effect (LATE).

Figure 2 – A prototypical RDD-Design



Source: WIFO-illustration.

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 $(\beta_{x<c}, \beta_{x>c})$. In this case, the baseline specification for an RDD is (see Cattaneo & Titiunik, 2022; Lee & Lemieux, 2010):

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

where 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:

1. 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;
2. only observations "close" to the cutoff by using an appropriately chosen bandwidth 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 less informative for the value of the expectation function at the cutoff.

Indeed, a recent survey by Cattaneo et al. (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 regarding 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 jump in other causal determinants of the outcome at the same GDP per 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 regions) just below (or above) the cutoff occurs. Such a pattern might indicate that there is a problem with the manipulation of the running variable. Formal methods to test for this have been proposed by McCrary (2008) and Cattaneo et al. (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).

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 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 EU cohesion policy interventions). 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 intention-to-treat effect further in the results section.

Nonetheless, the interest of the current study is the causal impact of structural funds expenditure. As pointed out, inter alia, by Cattaneo et al. (2019) this requires the use of a “fuzzy” RDD. This is a very similar approach to the sharp RDD but uses the cutoff as an “instrument” for expected treatment intensity. Essentially, this implies that in a first-stage regression an “expected treatment intensity” for the units left and right of the cutoff is estimated, similarly to the sharp RDD. This predicted treatment 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 – 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, and weighting of observations. Likewise, Cattaneo et al. (2019) suggest that also for a fuzzy RDD analysis, the baseline specification should be based on optimal bandwidth estimators using a triangular kernel for observations weights, and that specifications should be tested for their robustness regarding 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, the following assumptions must hold: (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. However, assumption (i) can be tested by examining the significance of the instrument $\mathrm{D_i}$ 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 has been calculated by DG-Regio and provides information on the EU's expenditure by NUTS-2 region separately for different funds and different uses, as well as in total (see Table 2 and The data on the percentage change in employment within enterprises from 2014 to the 2019/2020 period reveals minimal variation in growth rates across the average region within each region type. Specifically, between 2014 and 2019, employment in enterprises increased by an average of 9.8 percent in less developed regions, while both transitional regions experienced a growth rate of 8.5 percent, and more developed regions 8.8 percent. However, when examining the growth rate of employment in local units (as detailed in the last row), more distinct differences emerge. Employment in less developed regions increased by an average of 9.4 percent, whereas transitional regions experienced a growth of 15.8 percent. In contrast, more developed regions saw a significant increase, with employment rising by 20.0 percent.

Table 3 for descriptive statistics). In cases where the expenditure can be allocated directly to NUTS-2 regions, the data reports this expenditure exactly. If expenditures cannot be directly allocated to a NUTS-2 region (e.g., because they were used for a national program) it has been distributed at a per capita rate to regions of a country.

Our second data source is Eurostat, from where we extracted the following indicators for the years 2013 to 2020 (if available) at an annual frequency:

- the number of births and deaths of enterprises;
- the number of active enterprises (6);
- the number of local units (7);
- the number of employees in active enterprises and local units (8);
- the population average over the year; and
- the employment and unemployment rate (i.e., (un-)employment per population)

(6) The enterprise indicators are from Eurostat's regional business demography: https://doi.org/10.2908/BD_HGNACE2_R3

(7) The local unit indicators are from Eurostat's structural business statistics: https://doi.org/10.2908/SBS_R_NUTS06_R2

(8) (Regional) employment data for enterprises and local units is more focused on private sector employment than using variables as the employment rate, which also includes employment in public service and government agencies.

The basis for deciding whether a region was categorised as a less developed, transition or developed region was the average GDP at PPS for the years 2007 to 2009 in % of the EU average, as it was estimated at the time of the design of the program 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 asked Eurostat to provide us with vintage estimates of GDP at PPS. These are used as a running variable as well as to design the cutoff in the analysis below.

Finally, we also collect further variables to check for structural breaks in other variables that may be correlated to regional economic development. From ARDECO ([9]), we extracted information on GVA at current prices by industry (10 sectors), and employment by industry (10 sectors). From Eurostat sources we additionally collected data on the unemployment rate and the population by highest completed education ([10]) as well as by age groups (with the categories below 15 years, 15 to 64 and 65 or more years of age) as further variables that have been shown to impact business formation and regional entrepreneurship (Fritsch & Storey, 2014).

These data differ slightly in terms of scope and coverage. Thus, for the GDP and GVA indicators we have available all regions of the EU including the UK. By contrast, for the employment and unemployment rates we miss data on the UK (and for the unemployment rate also the Aland Islands - FI20). Furthermore, during the programming period there were some changes to the NUTS-2 classification. We therefore used the “NUTS converter”, a conversion tool developed by the Joint Research Centre (JRC) to consistently recode all values to the NUTS 2016 classification ([11]).

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

1. Cumulative number of enterprise births per 1000 inhabitants over the period 2014 to 2020;
2. Cumulative number of enterprise deaths per 1000 inhabitants over the period 2014 to 2020;
3. Change in the number of local units per 1000 inhabitants between 2014 and 2020;

([9]) „The Annual Regional Database of the European Commission (ARDECO)” provides consistent and harmonised time-series of demographic and socio-economic statistical data at the regional and sub-regional levels, see https://ur-ban.jrc.ec.europa.eu/ardeco/explorer.

([10]) 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.

([11]) 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).

4. Change in the number of enterprises per 1000 inhabitants between 2014 and 2020;
5. Percentage change of employment in enterprises between 2014 and 2020; and
6. Percentage change of employment in local units between 2014 and 2020.

One concern with respect to these indicators is that they include data extending into the COVID-19 pandemic of 2020. The measures taken to limit this pandemic led to a massive economic crisis that affected the member states and their regions to a different degree. 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 also conducted sharp and fuzzy RDD analyses for the outcome variables measured in terms of changes between 2014 and 2019.

Table 2 – Descriptive statistics on outcome variables

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	124	56	45.1	25.8	19.8	35.1	171.6
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	124	56	45.1	25.8	19.8	35.1	171.6
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	41	86	30.8	23.3	10.1	26.9	151.5
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	131	54	33.1	19.2	9.2	28.1	125.0
Change in number of local units per 1,000 inhabitants, 2014/2020	241	15	6.7	15.9	−92.0	5.7	103.2
Change in number of local units per 1,000 inhabitants, 2014/2019	241	15	4.7	16.0	−94.6	4.8	102.7
Change in number of enterprises per 1,000 inhabitants, 2014/2020	144	49	9.9	13.6	−77.0	7.4	60.6
Change in number of enterprises per 1,000 inhabitants, 2014/2019	144	49	8.3	12.7	−84.0	7.4	58.1
Change (%) in employment in enterprises, 2014/2020	144	49	6.8	12.1	−18.6	6.2	113.2
Change (%) in employment in	144	49	9.1	12.9	−26.8	8.4	117.8

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
enterprises, 2014/2019							
Change (%) in employment in local units, 2014/2020	240	15	12.8	83.4	−84.8	6.0	1147.2
Change (%) in employment in local units, 2014/2019	240	15	16.1	74.4	−91.4	9.6	990.4

Source: Eurostat; WIFO-calculations.

In our analysis of enterprise outcomes and formation, we encountered substantial challenges related to missing data. Specifically, regional information on enterprise variables, including active population, enterprise deaths, and births, is absent for 13 countries during the period from 2014 to 2020 ([12]). However, the dataset for local unit numbers is more complete, with the exception of the United Kingdom, which lacks data for 2019 and 2020. To mitigate data limitations, we designated 2014 as the "pre-funding" year instead of 2013, due to superior data availability in both indicator datasets for that year ([13]).

Table 2 provides a detailed overview of the sample distribution across all 281 NUTS-2 regions within the EU, including the UK, highlighting the data gaps we face. For instance, data on the cumulative number of enterprises per 1,000 inhabitants from 2014 to 2020 (and 2019, respectively) is available for only 124 NUTS-2 regions, indicating a lack of information from over 50% of the EU's NUTS-2 regions. The situation is more pronounced for enterprise deaths, where data is available for fewer than a quarter of the regions. Conversely, data on local units is more comprehensive, with information from 241 out of 281 NUTS-2 regions. This table underscores the need for caution in drawing inferences from enterprise data due to particularly low coverage.

The data on the percentage change in employment within enterprises from 2014 to the 2019/2020 period reveals minimal variation in growth rates across the average region within each region type. Specifically, between 2014 and 2019, employment in enterprises increased by an average of 9.8 percent in less developed regions, while both transitional regions experienced a growth rate of 8.5 percent, and more developed regions 8.8 percent. However, when examining the growth rate of employment in local units (as detailed in the last row), more distinct differences emerge. Employment in less developed regions increased by an average of 9.4 percent, whereas transitional regions experienced a growth of 15.8 percent. In contrast, more developed regions saw a significant increase, with employment rising by 20.0 percent.

([12]) These countries are Estonia, Latvia, Malta, Poland, Sweden, Belgium, Cyprus, Germany, Greece, Ireland, Luxembourg, Slovenia, and the United Kingdom.

([13]) This choice would pose a threat to our identification of cohesion policies' effects only if one were to assume that funding in the first year of the programming period would immediately and substantially manifest in enterprise numbers in this first year.

Table 3 also presents unweighted sample means and standard deviations for each indicator, categorised by region type (less developed, transitional, and more developed regions). The first row indicates that, on average, less developed regions experienced the establishment of 46.3 new enterprises per 1,000 inhabitants over the six-year period from 2014 to 2020. In comparison, transitional regions saw 44.7 new enterprises per 1,000 inhabitants, while more developed regions reported 44.5 new enterprises per 1,000 inhabitants.

Examining enterprise deaths per 1,000 inhabitants (rows 3 and 4), the data reveals that less developed regions experienced an average of 49.6 enterprise deaths per 1,000 inhabitants, compared to 21.2 in transitional regions and 28.7 in more developed regions between 2014 and 2020. Notably, when the period concludes in 2019, the mean differences between regions appear reduced.

Turning to data on local units, where coverage is more robust, the average less developed region reported an increase of 6.6 local units per 1,000 inhabitants in 2020 compared to 2014. This growth surpasses that of transitional regions slightly, which saw an increase of 6.0 per 1,000 inhabitants, and aligns closely with the growth observed in more developed regions, at 7.0 per 1,000 inhabitants.

The data on the percentage change in employment within enterprises from 2014 to the 2019/2020 period reveals minimal variation in growth rates across the average region within each region type. Specifically, between 2014 and 2019, employment in enterprises increased by an average of 9.8 percent in less developed regions, while both transitional regions experienced a growth rate of 8.5 percent, and more developed regions 8.8 percent. However, when examining the growth rate of employment in local units (as detailed in the last row), more distinct differences emerge. Employment in less developed regions increased by an average of 9.4 percent, whereas transitional regions experienced a growth of 15.8 percent. In contrast, more developed regions saw a significant increase, with employment rising by 20.0 percent.

Table 3 – Sample means and standard deviations by region type

	Less developed (N = 72)		Transition (N = 58)		More developed (N = 151)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Cumulative number of enterprise births per 1000 inhabitants, 2014–2020	46.3	26.7	44.7	28.5	44.5	24.7
Cumulative number of enterprise births per 1000 inhabitants, 2014–2019	46.3	26.7	44.7	28.5	44.5	24.7
Cumulative number of enterprise deaths per 1000 inhabitants, 2014–2020	49.6	46.1	21.2	6.1	28.7	10.0
Cumulative number of enterprise deaths per 1000 inhabitants, 2014–2019	35.2	17.9	31.9	22.8	31.2	19.2

	Less developed (N = 72)		Transition (N = 58)		More developed (N = 151)	
Change in number of local units per 1000 inhabitants, 2014/2020	6.6	13.2	6.0	18.3	7.0	16.5
Change in number of local units per 1000 inhabitants, 2014/2019	6.6	11.9	3.7	18.9	4.0	16.8
Change in number of enterprises per 1000 inhabitants, 2014/2020	8.1	16.9	10.5	8.7	10.8	12.7
Change in number of enterprises per 1000 inhabitants, 2014/2019	6.7	16.9	9.7	9.3	8.8	10.5
Change (%) in employment in enterprises, 2014/2020	6.7	19.2	7.3	8.0	6.6	6.4
Change (%) in employment in enterprises, 2014/2019	9.8	19.6	8.5	12.1	8.8	6.4
Change (%) in employment in local units, 2014/2020	5.7	28.3	14.5	72.4	16.0	104.7
Change (%) in employment in local units, 2014/2019	9.4	27.8	15.8	72.2	20.0	91.0

Source: Eurostat; WIFO-calculations.

Regions are categorised 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".

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 (i.e., funds received). This assumption can be directly tested by examining the statistical significance of the instrument (i.e., the dummy for the cutoff level) in Equation (3). Third, there should be no discontinuities in other variables at the same cutoff levels of GDP per 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

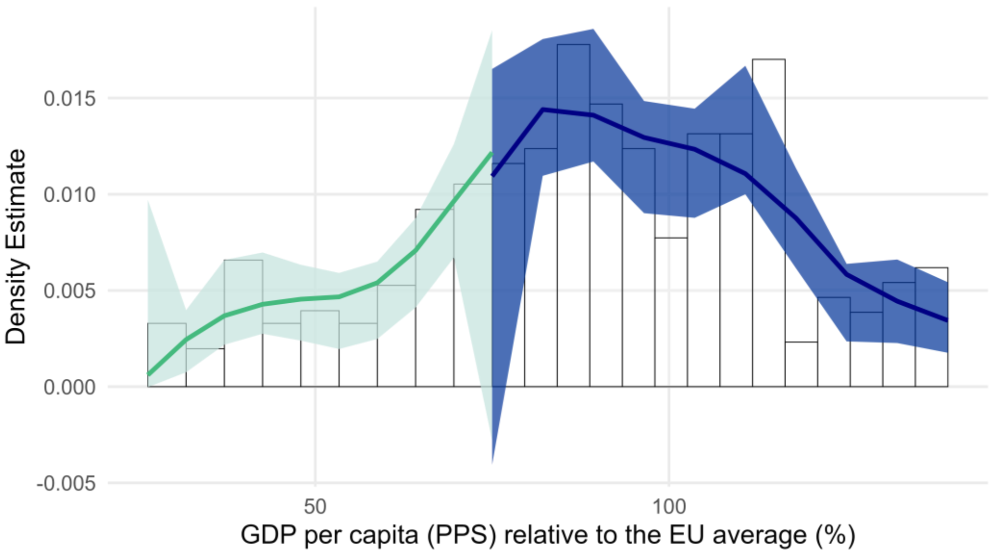
The first of these tests addresses the issue of regions' control over their treatment status. While such a manipulation may seem unlikely, it could occur if regions foresaw that funding conditions for regional policy would be substantially more generous for regions with a GDP per capita below 75% (respectively 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 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% and 90% cutoff.

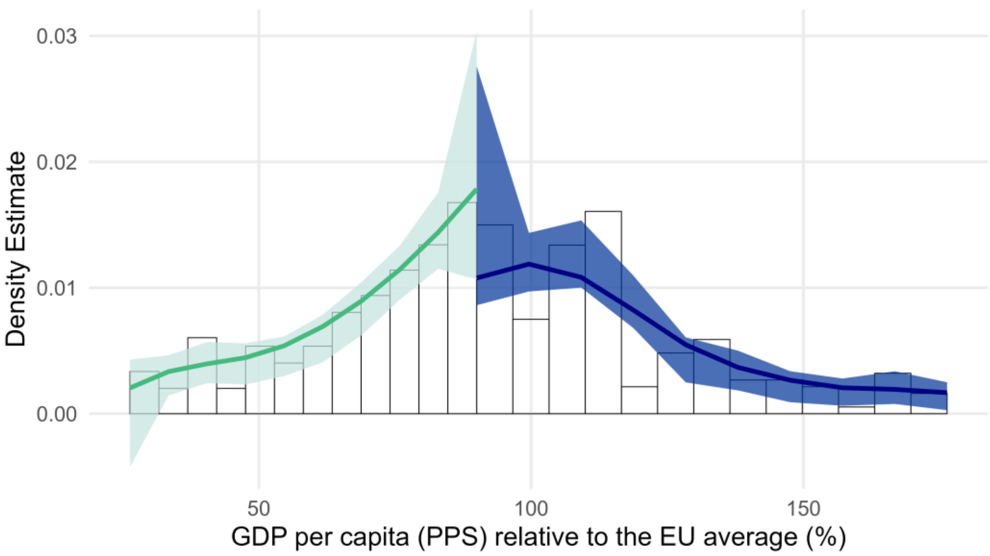
The bunching test by Cattaneo et al. (2020) uses this logic to test whether, based on the total distribution, the number of regions located at one side of the cutoff differs substantially from what could be expected if there was no cutoff at all. Figure 3 shows the results for the 75% cutoff in the upper panel, and the results for the 90% in the lower panel. In both these diagrams, the bars count the number of regions at each tick of the running variable, i.e., their 2007–2009 average GDP per capita relative to the EU average. The blue and green lines show the expected number at the respective tick, and the shaded area is the 95%-confidence interval for this fitted value.

Figure 3 – Test for manipulation of the running variable

Cutoff 75%



Cutoff 90%



Source: Eurostat; WIFO-calculations.

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 et al. (2020) suggests that the p-values of the null hypothesis of equal proportions of regions on both sides of the cutoff are 0.83 in the case of the 75% cutoff, and 0.74 at the 90% cutoff. Thus, the null 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 ([14]). To analyse instrument relevance, we inspect the results of the first-stage regression (Equation (3) above) for three specifications:

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”) for all observations. This specification is the least flexible and is equivalent to a simple 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 per capita below the cutoff and the running variable. In the following tables, 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 either side of the cutoff) and 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 et al. (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 et al. (2019). We refer to this specification as the *optimal bandwidth* specification in tables.

Table **4** 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

([14]) For robustness, we also test singular funds and expenditure types instead of all EU payments received, see Appendix A or details.

below this coefficient is the (nearest neighbour 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.

Table 4 – First stage regressions of Fuzzy RDD design

	75% cutoff			90% cutoff		
	Linear all	Quadratic all	Optimal bandwidth	Linear all	Quadratic all	Optimal bandwidth
EU expenditure per capita	1.058***	0.691	0.327	0.060	0.096	0.093
	(0.347)	(0.555)	(0.918)	(0.144)	(0.260)	(0.324)
EU expenditure in % of GDP	6.744***	4.305	4.866	0.604	0.760	0.174
	(2.419)	(3.869)	(6.394)	(1.005)	(1.699)	(1.852)
	Observations					
Left[1]	72	72	10	58	58	30 | 31
Right	58	58	12	151	151	26 | 30

Source: Eurostat, DG-Regio; 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 to 90 for the 75% cutoff and 75 to maximum for the 90% cutoff, uniform weighting; *Quadratic all* = quadratic functional form, bandwidth of 0 to 90 for the 75% cutoff and 75 to maximum for the 90% cutoff, uniform weighting; *Optimal bandwidth* = linear functional form, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors. [1] Effective observation to the left and the right of the respective cutoff; effective observations differ between treatment definitions in the case of 90% and optimal bandwidth and are separated by treatment with an "|".

The results suggest a low instrument relevance. The coefficients are statistically insignificant for all specifications at the 90% cutoff and in all specifications except for the "linear all" specification in the case of 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, with more flexible specifications, we cannot reject the null hypothesis of no difference in cohesion funding between regions right above and right below the 75% and 90% policy cutoffs.

This finding contrasts to prior evaluations using regression discontinuity designs to assess multiple EU Cohesion Policy intervention periods (e.g., Bachtrögler, 2016; Becker et al., 2010, 2012, 2018; Cerqua & Pellegrini, 2022; Ferrara et al., 2017; Pellegrini et al., 2013; Percoco, 2017) which did not include the 2014–2020 period. One potential explanation for this divergence is the limited sample size available for the analysis. Even when using all observation (irrespective of whether using the linear or the squared model variant), only 130 observations are available at the 75% cutoff, and 209 at the 90% cutoff. When applying the optimal bandwidth model, this number drops to 22 (respectively 56 and 61) effective observations ([15]).

Another plausible explanation lies in institutional and contextual changes during the 2014–2020 funding period. The introduction of transition regions created an intermediate category with distinct funding access, which likely reduced the sharpness of the discontinuity of treatment intensity at the 75% cutoff. Furthermore, recent evidence suggests that less developed regions grew more affluent while transition regions experienced relative declines prior to his funding period (European Commission, 2024). These dynamics may have diluted the funding disparities between less developed and transition regions compared to earlier periods.

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

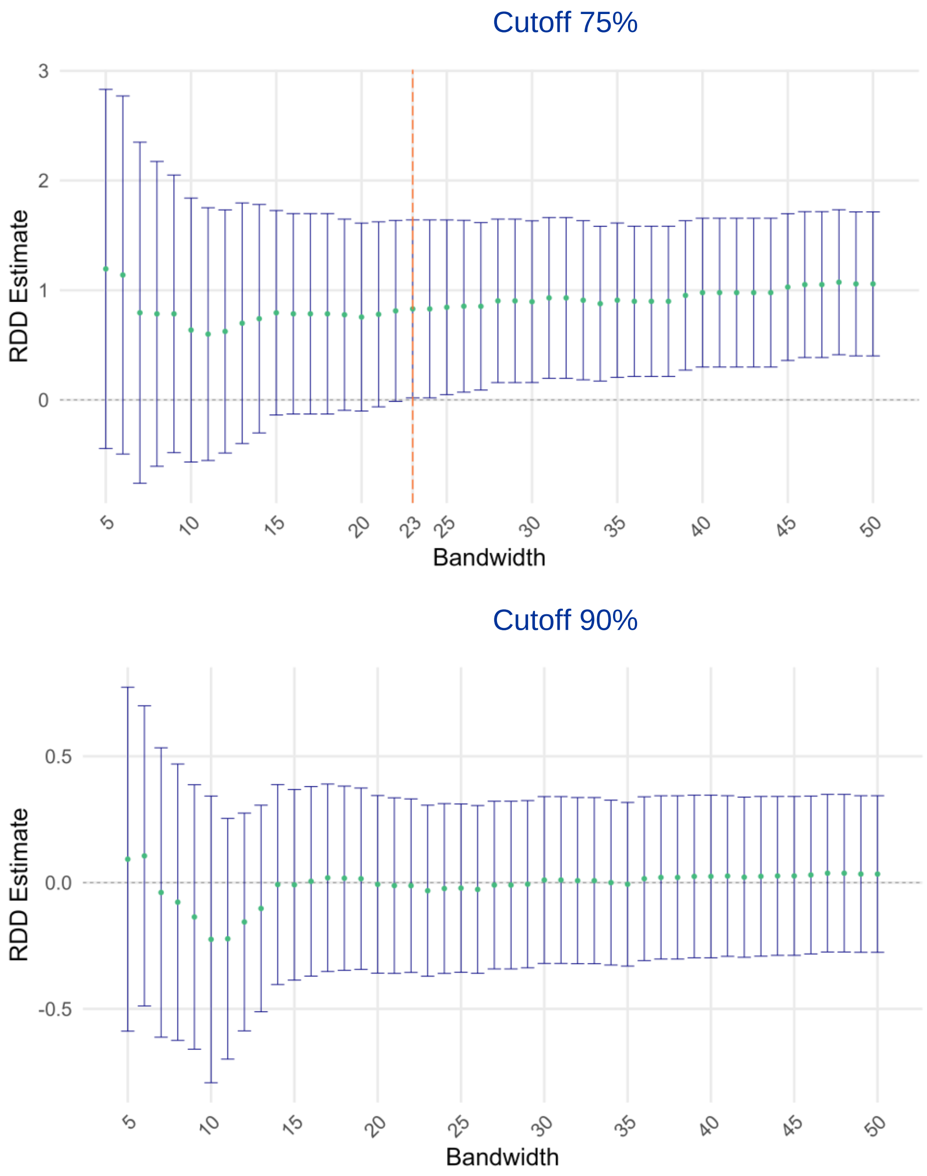
Since this result is detrimental to the aim of our study, additional robustness checks were undertaken to see whether this insignificance of the instrument can be avoided by using other definitions of the cutoff variable and/or by focusing only on some funds or some purposes of the funds. These additional results pertain to i) using individual funds to define the payments variables, ii) using an alternative cutoff measure considering only regions that were classified as less developed or transition regions in the actual implementation of the programme, and iii) focusing only on certain expenditure types. They are reported in the annex and do not differ from those reported here.

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. Figure 4 plots the evolution of the coefficient across these bandwidths as red dots, along with 95% confidence intervals. 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 +/– 23 percentage points from the cutoff. This is quite far from the suggested data-driven optimal bandwidth of +/– 3.6 percentage points.

([15]) Interestingly, despite the general findings of a mild positive effect of cohesion policy in many RDD-studies (see Ehrlich & Overman, 2020 for an overview) a recent study by Albanese et al. (2025) 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.

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.

Figure 4 – Simulation of tests for instrument relevance in dependence of the chosen bandwidth in the linear model



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

5.3. Structural breaks 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 enterprise and employment growth in the light of the pertinent literature on regional development (see, e.g., Cuaresma et al., 2014; Fritsch & Storey, 2014; Koellinger & Roy Thurik, 2012). These are:

1. Sector shares of agriculture, manufacturing, and services in GVA and employment in 2013, since overall differences in founding of new enterprises could be related to structural differences in sector composition;
2. Population shares by highest completed education, where we coded persons, whose highest completed education is ISCED 2 or lower as “less educated”, ISCED levels 3 and 4 as “middle educated” and ISCED level 5 or higher[16]) as “highly educated”. A higher educated population supposedly impacts innovation and start-up creation;
3. The age structure of the population with the share of population below 15 (“Young”), the share of working age population 15 to 64 (“Working age”), and the share of population aged 65 or older (“Senior”);
4. The stock of number of enterprises and local units per 1,000 inhabitants in 2013; and
5. The employment and unemployment rates in 2013.

Table 5 – Placebo tests for breaks for other variables at the cutoffs

	75% cutoff			90% cutoff		
	Linear all	Quadratic all	Optimal bandwidth	Linear all	Quadratic all	Optimal bandwidth
	2013 employment shares of					
Agriculture	0.012	0.086*	0.088	0.010	−0.005	−0.035
	(0.029)	(0.049)	(0.071)	(0.019)	(0.027)	(0.034)
Production	0.003	−0.096**	−0.125**	−0.074***	−0.018	−0.029
	(0.03)	(0.045)	(0.056)	(0.017)	(0.025)	(0.036)
Services	−0.001	−0.008	−0.023**	0.010	0.001	−0.002
	(0.005)	(0.011)	(0.012)	(0.01)	(0.008)	(0.008)
	2013 GVA shares of					
Agriculture	0.000	0.018*	0.023*	0.001	−0.006	−0.004
	(0.007)	(0.011)	(0.014)	(0.007)	(0.01)	(0.009)
Production	−0.043	−0.173**	−0.207**	−0.097***	0.001	−0.016
	(0.04)	(0.068)	(0.086)	(0.023)	(0.034)	(0.042)
Services	−0.003	−0.015	−0.013	0.005	0.002	0.006
	(0.005)	(0.009)	(0.012)	(0.004)	(0.005)	(0.006)
	2013 population shares of					
Middle educated	−0.032	−0.177**	−0.126	−0.063**	−0.017	−0.047
	(0.057)	(0.079)	(0.093)	(0.032)	(0.054)	(0.071)
Less educated	0.039	0.214**	0.138	0.045	−0.014	−0.023
	(0.063)	(0.089)	(0.108)	(0.036)	(0.06)	(0.068)
Highly educated	−0.007	−0.037	−0.011	0.018	0.031	0.073*
	(0.021)	(0.03)	(0.037)	(0.019)	(0.023)	(0.044)
	2013 population shares of					
Young	0.007	0.009	−0.004	0.015**	0.010	0.005
	(0.008)	(0.011)	(0.011)	(0.006)	(0.01)	(0.017)
Working age	0.006	−0.017	−0.017	−0.007	−0.004	0.000
	(0.008)	(0.013)	(0.018)	(0.007)	(0.012)	(0.015)

[16]) ISCED is the international standard classification of educational degrees that ensures comparability of educational data across countries.

	75% cutoff			90% cutoff		
Senior	−0.013	0.008	0.016	−0.008	−0.005	−0.005
	(0.012)	(0.016)	(0.019)	(0.01)	(0.016)	(0.019)
	Employment & Unemployment rate (levels, 2013)					
Unemployment	0.045	0.075	0.054	0.043*	0.039	0.046
	(0.033)	(0.053)	(0.071)	(0.024)	(0.041)	(0.051)
Employment	−0.031	−0.069	−0.029	−0.048***	−0.028	−0.009
	(0.026)	(0.044)	(0.061)	(0.017)	(0.023)	(0.034)
	Number of establishments per 1,000 inhabitants (levels, 2013)					
Local units	23.192***	22.699*	4.667	−3.512	1.956	−7.797
	(8.128)	(12.781)	(18.989)	(6.151)	(7.773)	(12.017)
Enterprises	−1.880	−2.740	−2.215	−5.115	−5.597	−11.892
	(10.684)	(16.688)	(16.247)	(7.547)	(8.604)	(10.577)

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 to 90 for the 75% cutoff and 75 to maximum for the 90% cutoff, uniform weighting; *Quadratic all* = quadratic functional form, bandwidth of 0 to 90 for the 75% cutoff and 75 to maximum for the 90% cutoff, uniform weighting; *Optimal bandwidth* = linear functional form, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

In our analysis, we applied the same three models previously utilized to assess each of these variables, with the results presented in Table 5. Some models yielded statistically significant coefficients, allowing us to reject the null hypothesis of no structural break at the respective cutoffs. This indicates that these structural variables exhibit discontinuities at the same thresholds used to determine the intensity of cohesion policy funding, complicating the isolation of causal effects attributable to such funding.

Specifically, at the 75% cutoff, we can reject the null hypothesis of no break for certain specifications related to sectoral employment shares and the proportions of highly and low-educated individuals. Of particular concern for our identification strategy regarding the effects of cohesion policy on business growth is the rejection of the null hypothesis for the number of local units in 2013. If the initial levels of business numbers in 2013 structurally differed between regions on either side of the cutoff, any estimates of their performance over the subsequent period cannot be convincingly attributed to cohesion policy funding.

At the 90% cutoff, structural breaks are evident in various indicators, including the employment and GVA shares of the production sector, the proportions of medium and highly educated individuals, the share of the young population, and both employment and unemployment rates. These findings particularly caution against associating cohesion policy funding during the 2014–2020 period with employment growth metrics, as employment levels already differed at the outset of the period.

In conclusion, the results from this series of placebo tests highlight significant further cautionary signals against a causal interpretation of results from a Regression Discontinuity Design. It remains possible that observed impacts of cohesion policy funding may be attributed to discontinuous changes in other influential variables at the cutoff, rather than the policies themselves.

6. Estimation 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 (ITT)“ effect rather than the treatment effect. Methodologically, this entails transitioning from a fuzzy RDD to a sharp RDD approach, or equivalently, concentrating on the reduced form of the fuzzy RDD. To investigate this possibility, Table 6 and Table 7 present the results from estimating Equation (2) using the same three specifications previously discussed.

In the specification employing the 75% cutoff, we do not observe any statistically significant coefficients, indicating an inability to discern any meaningful effects of cohesion policy at this threshold, as none of the coefficients in Table 6 differ significantly from zero. However, at the 90% cutoff, certain coefficients achieve statistical significance:

(1) The cumulative number of enterprise births per 1,000 inhabitants from 2014 to 2020 is marginally statistically significant in the quadratic all specification, which uses a quadratic functional form and includes all observations with a relative initial GDP exceeding 75% of the EU average. This coefficient suggests that transitional regions had 20 *fewer* enterprises per 1,000 inhabitants founded compared to more developed regions.

(2) The cumulative number of enterprise deaths per 1,000 inhabitants over the same period is marginally statistically significant in the linear all specification, employing a linear functional form with all observations having a relative initial GDP above 75% of the EU average. This suggests that transitional regions experienced 5.7 *fewer* enterprise deaths per 1,000 inhabitants than more developed regions ([17]).

(3) The change in the number of active enterprises per 1,000 inhabitants between 2014 and 2020, as well as between 2014 and 2019, is statistically significant at the 5% level in the linear all specification. These coefficients indicate that transitional regions had approximately seven *more* active enterprises per 1,000 inhabitants in 2019/2020 compared to 2014 than more developed regions.

([17]) It is worth briefly noting that the simultaneous observation of increased/decreased enterprise births and deaths in regions, indicative of heightened or lowered "enterprise churning," aligns with expectations set forth in the entrepreneurship literature (e.g., Parker, 2007; Reiner et al., 2020). This phenomenon suggests a dynamic business environment where the entry and exit of enterprises occur at elevated rates, reflecting both the challenges and opportunities present within the market.

(4) The percentage change in employment within enterprises from 2014 to 2020 is statistically significant at the 5% level in the quadratic all specification. This coefficient suggests that transitional regions experienced approximately 9% *less* employment growth in enterprises than more developed regions.

Although certain coefficients achieve statistical significance in some specifications, caution is warranted in interpreting these estimates. The lack of consistent significance across specifications suggests a high sensitivity of results to the functional form. Moreover, the direction of the effect's sign is not maintained across specifications. Combined with pre-test results indicating structural breaks in other potential causal variables, this underscores the necessity for careful consideration when attributing causal interpretations to these findings.

Table 6 – Intention-to-treat-effect of EU cohesion policies at the 75% cutoff (Sharp RDD)

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	10.163	14.403	18.786	62
	(11.427)	(13.555)	(14.768)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	10.163	14.403	18.786	62
	(11.427)	(13.555)	(14.768)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	21.281	99.321	−7.042	19
	(21.986)	(153.567)	(18.85)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	2.253	6.197	11.290	81
	(8.922)	(11.112)	(16.512)	
Change in number of local units per 1,000 inhabitants, 2014/2020	1.879	−4.122	−8.027	114
	(4.468)	(5.298)	(7.275)	
Change in number of local units per 1,000 inhabitants, 2014/2019	5.241	−0.453	−9.977	114
	(4.698)	(5.053)	(7.677)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	3.046	4.434	6.498	71
	(5.415)	(5.062)	(5.959)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	2.628	5.870	7.425	71
	(5.407)	(4.786)	(4.962)	
Change (%) in employment in Enterprises, 2014/2020	−1.990	15.051	14.020	71
	(6.467)	(10.295)	(10.294)	
Change (%) in employment in Enterprises, 2014/2019	−3.267	13.529	14.176	71
	(6.974)	(10.723)	(10.32)	
Change (%) in employment in Local units, 2014/2020	5.950	−7.715	1.810	113
	(14.143)	(10.514)	(11.571)	
Change (%) in employment in Local units, 2014/2019	5.443	−2.736	0.010	113
	(13.977)	(9.909)	(9.471)	

Source: Eurostat, 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 to 90, uniform weighting; *Quadratic all* = quadratic functional form, bandwidth of 0 to 90, uniform weighting; *Optimal bandwidth* = linear functional form, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

Table 7 – Intention-to-treat-effect of EU cohesion policies at the 90% cutoff (Sharp RDD)

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	8.431	−20.032*	−4.178	80
	(11.291)	(10.516)	(3.658)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	8.431	−20.032*	−4.178	80
	(11.291)	(10.516)	(3.658)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	−5.690*	−11.309	−1.631	32
	(3.285)	(13.363)	(5.092)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	2.617	−11.051	−18.819	70
	(9.124)	(10.952)	(14.933)	
Change in number of local units per 1,000 inhabitants, 2014/2020	5.875	6.041	11.182	170
	(7.967)	(10.037)	(10.807)	
Change in number of local units per 1,000 inhabitants, 2014/2019	6.131	5.999	5.510	170
	(8.061)	(10.415)	(9.598)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	6.955**	−5.246	5.809	98
	(3.338)	(4.509)	(6.104)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	7.181**	−3.665	6.338	98
	(3.186)	(3.957)	(5.041)	
Change (%) in employment in Enterprises, 2014/2020	0.382	−8.858**	−6.322	98
	(2.741)	(4.157)	(5.02)	
Change (%) in employment in Enterprises, 2014/2019	−0.989	−9.662	−7.732	98
	(5.148)	(8.898)	(8.657)	
Change (%) in employment in Local units, 2014/2020	9.412	12.729	29.760	170
	(35.831)	(44.587)	(33.142)	
Change (%) in employment in Local units, 2014/2019	6.217	6.401	16.532	170
	(34.817)	(43.468)	(35.349)	

Source: Eurostat, 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

6.2. Fuzzy RDD: the treatment effect

The findings from the fuzzy regression discontinuity design (RDD) for both the 75% cutoff (as detailed in Table 8) and the 90% cutoff (shown in Table 9) further underscore the lack of robustness exhibited by the sharp RDD approach. These results suggest that our analytical demands on the data may exceed its capacity to yield reliable insights.

Across both cutoffs, the coefficients consistently lack statistical significance, occasionally exhibiting counterintuitive signs and magnitudes. Furthermore, the coefficients frequently change sign between different specifications, indicating instability and undermining the reliability of any derived conclusions. This variability highlights the inherent limitations in the dataset and calls into question the feasibility of drawing definitive causal inferences from this analysis.

Table 8 – Treatment effect of EU cohesion policies at the 75% cutoff (Fuzzy RDD)

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	27.554	909.713	37.004	62
	(29.718)	(46947.028)	(91.372)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	27.554	909.713	37.004	62
	(29.718)	(46947.028)	(91.372)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	13.841	84.586	−10.897	19
	(16.292)	(264.344)	(38.699)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	5.131	−276.586	14.852	81
	(15.27)	(10129.684)	(14.913)	
Change in number of local units per 1,000 inhabitants, 2014/2020	2.220	−10.641	−40.289	114
	(5.198)	(20.68)	(104.738)	
Change in number of local units per 1,000 inhabitants, 2014/2019	6.190	−1.169	33.066	114
	(5.605)	(13.247)	(50.008)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	6.343	−75.610	12.884	71
	(10.538)	(1057.948)	(41.663)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	5.472	−100.110	15.995	71
	(10.099)	(1391.991)	(49.786)	
Change (%) in employment in Enterprises, 2014/2020	−4.144	−256.667	24.751	71
	(15.189)	(3474.147)	(68.652)	
Change (%) in employment in Enterprises, 2014/2019	−6.803	−230.719	25.666	71
	(18.019)	(3129.396)	(71.674)	
Change (%) in employment in Local units, 2014/2020	6.887	−23.460	6.341	113
	(16.213)	(50.926)	(37.047)	
Change (%) in employment in Local units, 2014/2019	6.300	−8.321	5.590	113
	(15.987)	(34.27)	(32.044)	

Source: Eurostat, DG-Regio, 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 to 90, uniform weighting; *Quadratic all* = quadratic functional form, bandwidth of 0 to 90, uniform weighting; *Optimal bandwidth* = linear functional form, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

In conclusion, we determine that the fuzzy regression discontinuity design (RDD) approach, despite its theoretical appeal, fails to deliver valid results due to the lack of instrument validity. Consequently, this method does not allow us to draw any definitive conclusions regarding the causal impact of cohesion policy funding on enterprises. The inherent limitations and inconsistencies in the data and analysis underscore the challenges in establishing a reliable causal link through this approach ([18]).

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

Table 9 – Treatment effect of EU cohesion policies at the 90% cutoff (Fuzzy RDD)

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	−19.912	43.996	−1.771	80
	(32.989)	(31.887)	(15.884)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	−19.912	43.996	−1.771	80
	(32.989)	(31.887)	(15.884)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	−152.781	141.958	−4.313	32
	(262.817)	(508.688)	(13.984)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	−13.503	99.491	−327.154	70
	(59.215)	(408.037)	(2300.055)	
Change in number of local units per 1,000 inhabitants, 2014/2020	49.413	25.521	−1075.989	170
	(92.443)	(50.526)	(44279.634)	
Change in number of local units per 1,000 inhabitants, 2014/2019	51.561	25.345	−132.395	170
	(91.29)	(48.772)	(1435.606)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	−76.647	−126.333	−43.158	98
	(182.49)	(1395.367)	(80.111)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	−79.140	−88.259	−40.281	98
	(193.733)	(1002.356)	(82.023)	
Change (%) in employment in Enterprises, 2014/2020	−4.206	−213.296	−236.646	98
	(31.566)	(2344.903)	(3063.794)	
Change (%) in employment in Enterprises, 2014/2019	10.897	−232.661	−245.061	98
	(54.863)	(2625.3)	(2708.077)	
Change (%) in employment in Local units, 2014/2020	79.157	53.777	−260.290	170
	(296.46)	(188.893)	(978.532)	
Change (%) in employment in Local units, 2014/2019	52.282	27.040	−112.236	170
	(282.602)	(179.369)	(410.817)	

Source: Eurostat, DG-Regio, 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 75 to maximum, uniform weighting; *Quadratic all* = quadratic functional form, bandwidth of 75 to maximum, uniform weighting; *Optimal bandwidth* = linear functional form, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

7. Robustness checks

We also conducted various robustness tests and additional analyses for both the sharp and fuzzy RDD approach ([19]). These included:

- Considering sample splits by average education. Here we separate regions which had an above and below median share of less educated residents in 2013 because Becker et al. (2012) indicate that treatment effects may vary by educational attainment.

([19]) Given the low reliability of fuzzy RDD results below, we report only the results of the sharp RDD (i.e., the intention-to-treat effect).

- An analysis of the impact of potential outliers on result by focusing only on regions in member states that were EU members already before 2004 ([20]).

The additional robustness checks, detailed in the annex, yield limited new insights. When the sample is divided based on regions with below and above median education levels, no statistically significant results emerge at either the 75% or 90% cutoffs. This lack of significance is likely attributable to the further reduction in the number of observations when the sample is split.

However, when the analysis is concentrated on regions within countries that were EU members before 2004, particularly at the 90% cutoff, several coefficients achieve statistical significance. The most consistently robust finding pertains to the cumulative number of enterprise deaths per 1,000 inhabitants from 2014 to 2019. In both the quadratic and optimal bandwidth specifications, it is observed that regions just below the 90% cutoff (and thus transitional regions) experienced approximately 17 fewer enterprise deaths per 1,000 inhabitants compared to regions just above the 90% cutoff (and thus more developed regions).

As Appendix A suggests, instrument validity is (occasionally) more stable using individual funds/expenditures. We have therefore also estimated "fuzzy RDDs" for each of these funds and expenditure types (with both our measures of treatment intensity, i.e., per capita, and as % of GDP). In these 1320 estimated regressions, the effects of the second stage are statistically significant at the 10% significance level in only 13 regressions and are furthermore not robust across different specifications. Due to this lack of robustness and consistency, we do not present the results in more detail.

8. Summary and Discussion

In conclusion, this study reveals that evaluating the impact of cohesion policies on enterprises in the 2014–2020 programming period through a regression discontinuity design (RDD) results in largely inconclusive findings. While some coefficients suggest minor positive effects of these policies on enterprise formation and employment, these effects are only weakly significant and lack robustness across various specifications.

Moreover, pretests designed to validate the assumptions necessary for causal interpretation of RDD estimations indicate that such interpretations are contingent on strong assumptions. This limitation applies to both sharp RDD estimates, which focus on the intention-to-treat effect, and fuzzy RDDs, which concentrate on the average treatment effect.

([20]) 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.

For the sharp RDD, we reject the null hypothesis that other critical variables, such as the initial number of local units and sectoral structure indicators – known to influence regional and enterprise growth – are continuous at the 75% and 90% cutoffs relevant to cohesion policy. This suggests the presence of parallel discontinuities in these variables at these thresholds, complicating the determination of whether the observed effects are due to these variables or the discontinuity in funding availability.

In the case of the fuzzy RDD, additional tests for instrument relevance indicate significant jumps in treatment intensity at the 75% cutoff only when all regions are included in the analysis, assuming a linear functional form for the forcing variable and uniform observation weighting. However, the statistical significance of this effect diminishes when applying more data-demanding models typically used in the literature. When employing more flexible functional forms, kernels that prioritize observations near the cutoff, or data-driven bandwidth selections, the results lose statistical significance.

In particular, the lacking statistical significance of the discontinuity in treatment intensity near the 75% and 90% thresholds suggests that the few 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 the reduction of economic disparities between less developed regions (that grew more affluent before the funding period), and transition regions (that tended to fall behind), may have “diluted” the sharpness of eligibility thresholds in cohesion policy. This structural feature of the 2014–2020 policy context, specifically, the absence of a pronounced discontinuity in funding intensity at the eligibility thresholds, fundamentally limits the applicability and statistical power of the RDD approach in this evaluation period.

Future evaluations of Cohesion Policy will therefore have to carefully scrutinize the validity ofthe assumptions used to identify RDDs, particularly as eligibility criteria evolve. In addition, expanding analyses to include multiple programming periods or longer post-treatment horizons could enhance statistical power and reliability of such evaluations.

9. References

Albanese, G., Carrieri ,Vincenzo, Rita Ferrara ,Antonella, & and Speziali, M. M. (2025). Beyond GDP: Assessing the impact of the 2007–13 EU Cohesion Policy. *Regional Studies*, *59*(1), 1–21. https://doi.org/10.1080/00343404.2024.2352532

Bachtrögler, J. (2016). *On the effectiveness of EU structural funds during the Great Recession: Estimates from a heterogeneous local average treatment effects framework*. WU Department of Economics Working Paper No. 230.

Becker, S. O., Egger, P. H., & von Ehrlich, M. (2010). Going NUTS: The effect of EU Structural Funds on regional performance. *Journal of Public Economics*, *94*(9), 578–590. https://doi.org/10.1016/j.jpubeco.2010.06.006

Becker, S. O., Egger, P. H., & von Ehrlich, M. (2012). Too much of a good thing? On the growth effects of the EU's regional policy. *European Economic Review*, *56*(4), 648–668. https://doi.org/10.1016/j.euroecorev.2012.03.001

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

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica*, *82*(6), 2295–2326. https://doi.org/10.3982/ECTA11757

Cattaneo, M. D., Idrobo, N., & Titiunik, R. (2019). *A Practical Introduction to Regression Discontinuity Designs: Foundations*. https://doi.org/10.1017/9781108684606

Cattaneo, M. D., Jansson, M., & Ma, X. (2020). Simple Local Polynomial Density Estimators. *Journal of the American Statistical Association*, *115*(531), 1449–1455. https://doi.org/10.1080/01621459.2019.1635480

Cattaneo, M. D., & Titiunik, R. (2022). Regression Discontinuity Designs. *Annual Review of Economics*, *14*(1), 821–851. https://doi.org/10.1146/annurev-economics-051520-021409

Cerqua, A., & Pellegrini, G. (2022). How much does state aid mitigate employment losses? Local policy effects at a time of economic crisis. *Regional Studies*, *56*(10), 1698–1712. https://doi.org/10.1080/00343404.2021.2003319

Cuaresma, J. C., Doppelhofer, G., & Feldkircher, M. (2014). The Determinants of Economic Growth in European Regions. *Regional Studies*, *48*(1), 44–67. https://doi.org/10.1080/00343404.2012.678824

Cunningham, S. (2021). *Causal inference: The mixtape*. Yale university press.

Ehrlich, M. v, & Overman, H. G. (2020). Place-Based Policies and Spatial Disparities across European Cities. *Journal of Economic Perspectives*, *34*(3), 128–149. https://doi.org/10.1257/jep.34.3.128

European Commission. (2015). *European Structural and Investment Funds 2014-2020: Official texts and commentaries*. Publications Office of the European Union.

European Commission (Ed.). (2016). *Measuring the impact of Structural and Cohesion Funds using the Regression Discontinuity Design – Ex post evaluation of Cohesion Policy programmes 2007-2013, focusing on the European Regional Development Fund (ERDF) and the Cohesion Fund (CF)*. Publications Office of the European Union.

European Commission. (2024). *Ninth report on economic, social and territorial cohesion.* Publications Office. https://data.europa.eu/doi/10.2776/264833

European Court of Auditors. (2019). *Allocation of Cohesion policy funding to Member States for 2021-2027* (Rapid Case Review).

Ferrara, A. R., McCann, P., Pellegrini, G., Stelder, D., & Terribile, F. (2017). Assessing the impacts of Cohesion Policy on EU regions: A non-parametric analysis on interventions promoting research and innovation and transport accessibility. *Papers in Regional Science*, *96*(4), 817–842. https://doi.org/10.1111/pirs.12234

Fritsch, M., & Storey, D. J. (2014). Entrepreneurship in a Regional Context: Historical Roots, Recent Developments and Future Challenges. *Regional Studies*, *48*(6), 939–954. https://doi.org/10.1080/00343404.2014.892574

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

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, *69*(1), 201–209. https://www.jstor.org/stable/2692190

Hennicke, M., & Krause, W. (2024). *nuts: Convert European Regional Data* [R]. https://docs.ropensci.org/nuts/

Joint Research Centre. (2022). *NUTS converter*. https://urban.jrc.ec.europa.eu/tools/nuts-converter

Koellinger, P. D., & Roy Thurik, A. (2012). Entrepreneurship and the business cycle. *Review of Economics and Statistics*, *94*(4), 1143–1156. https://direct.mit.edu/rest/article-abstract/94/4/1143/58039

Lang, V., Redeker, N., & Bischof, D. (2023). *Place-based policies and inequality within regions*. https://doi.org/10.31219/osf.io/2xmzj

Lee, D. S., & Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, *48*(2), 281–355. https://www.aeaweb.org/articles?id=10.1257/jel.48.2.281

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, *142*(2), 698–714. https://www.sciencedirect.com/science/article/pii/S0304407607001133

Parker, S. (Ed.). (2007). *The Life Cycle of Entrepreneurial Ventures*. Springer US. https://doi.org/10.1007/978-0-387-32313-8

Pellegrini, G., Terribile, F., Tarola, O., Muccigrosso, T., & Busillo, F. (2013). Measuring the effects of European Regional Policy on economic growth: A regression discontinuity approach. *Papers in Regional Science*, *92*(1), 217–234. https://www.sciencedirect.com/science/article/pii/S1056819023012423

Percoco, M. (2017). Impact of European Cohesion Policy on regional growth: Does local economic structure matter? *Regional Studies*, *51*(6), 833–843. https://doi.org/10.1080/00343404.2016.1213382

Reiner, C., Kronenberg, C., & Gassler, H. (2020). The Spatial Dimension of Entrepreneurship: Stylized Facts for the Case of Austria. *Economic and Business Review*, *22*(2), 3. https://www.ebrjournal.net/home/vol22/iss2/3/

10. Appendices

10.1. Appendix A: First stage regressions for alternative funds, expenditure types, and different treatment definitions

Table A 1 – First stage regressions for alternative funds (using different treatment intensity measures)

	75% cutoff			90% cutoff		
	Linear all	Quadratic all	Optimal bandwidth	Linear all	Quadratic all	Optimal bandwidth
Exp. excl. REACT / capita	1.006***	0.533	0.377	0.063	0.132	0.080
	(0.306)	(0.504)	(0.837)	(0.125)	(0.217)	(0.259)
Exp. excl. REACT / GDP	6.501***	2.986	4.811	0.547	0.988	0.160
	(2.191)	(3.573)	(5.88)	(0.915)	(1.471)	(1.558)
Cohesion funds exp. / capita	0.194**	−0.061	−0.040	−0.006	0.052	−0.005
	(0.079)	(0.124)	(0.2)	(0.041)	(0.056)	(0.035)
Cohesion funds exp. / GDP	1.126*	−0.806	−0.055	0.041	0.405	−0.026
	(0.607)	(0.951)	(1.421)	(0.348)	(0.449)	(0.249)
ERDF exp. / capita	0.568***	0.355	0.213	0.056	0.063	0.093
	(0.198)	(0.319)	(0.536)	(0.082)	(0.151)	(0.192)
ERDF exp. / GDP	3.713***	2.110	2.649	0.363	0.462	0.240
	(1.350)	(2.174)	(3.777)	(0.506)	(0.927)	(1.062)
YEI exp./ capita	0.014**	0.019*	0.023*	0.007	0.003	0.009
	(0.007)	(0.01)	(0.013)	(0.006)	(0.01)	(0.014)
YEI exp. / GDP	0.100	0.155	0.223	0.049	0.016	0.036
	(0.042)	(0.061)	(0.076)	(0.031)	(0.052)	(0.072)
N	130	130	130	209	209	209

Source: Eurostat, DG-Regio; 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

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

	75% cutoff			90% cutoff		
	Linear all	Quadratic all	Optimal bandwidth	Linear all	Quadratic all	Optimal bandwidth
AIS exp. / capita	0.140*	0.250**	0.302**	−0.021	−0.054	−0.088
	(0.077)	(0.125)	(0.135)	(0.02)	(0.035)	(0.062)
AIS exp. / GDP	0.845	2.058**	2.458***	−0.076	−0.307	−0.560
	(0.535)	(0.827)	(0.776)	(0.116)	(0.216)	(0.413)
Human capital exp. / capita	0.247***	0.294**	0.249	0.011	−0.018	−0.026
	(0.095)	(0.146)	(0.186)	(0.039)	(0.074)	(0.087)
Human capital exp. / GDP	1.677***	2.112**	2.134	0.175	−0.088	−0.245
	(0.626)	(0.956)	(1.316)	(0.233)	(0.444)	(0.493)
Infrastructure exp. / capita	0.260*	0.169	−0.127	0.045	0.055	0.093
	(0.139)	(0.199)	(0.374)	(0.056)	(0.117)	(0.12)
Infrastructure exp. / GDP	1.635*	1.158	0.078	0.226	0.265	0.380
	(0.958)	(1.391)	(2.567)	(0.352)	(0.718)	(0.683)
RTD exp./ capita	0.162***	0.031	0.089	0.02	0.043	0.065
	(0.049)	(0.082)	(0.129)	(0.026)	(0.037)	(0.062)
RTD exp. / GDP	1.201***	−0.011	0.727	0.174	0.363	0.230
	(0.351)	(0.596)	(0.904)	(0.164)	(0.221)	(0.201)
Techn. Assistance exp. / capita	0.034***	0.015	0.014	−0.001	0.005	−0.001
	(0.009)	(0.014)	(0.022)	(0.004)	(0.005)	(0.006)
Techn. Assistance exp. / GDP	0.226***	0.094	0.141	0.007	0.043	−0.004
	(0.062)	(0.104)	(0.163)	(0.030)	(0.041)	(0.040)
Transportation exp. / capita	0.216***	−0.068	−0.011	0.006	0.065	0.011
	(0.070)	(0.121)	(0.208)	(0.035)	(0.049)	(0.031)
Transporation exp. / GDP	1.16**	−1.105	0.139	0.099	0.484	0.118
	(0.538)	(0.905)	(1.473)	(0.302)	(0.396)	(0.245)
N	130	130	130	209	209	209

Source: Eurostat, DG-Regio; 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

Table A 3 – Treatment effect of EU cohesion policy at the 75% cutoff (Fuzzy RDD)

EU expenditures as % of GDP as measure of treatment intensity

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	9.403	−6.45	4.912	62
	(32.455)	(23.503)	(11.32)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	9.403	−6.45	4.912	62
	(32.455)	(23.503)	(11.32)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	2.852	21.585	−2.153	19
	(3.941)	(78.713)	(8.255)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	1.413	−2.277	2.575	81
	(3.301)	(8.83)	(4.042)	
Change in number of local units per 1,000 inhabitants, 2014/2020	0.328	−1.499	−1.336	114
	(0.778)	(3.079)	(1.85)	
Change in number of local units per 1,000 inhabitants, 2014/2019	0.916	−0.165	−3.62	114
	(0.853)	(1.888)	(6.025)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	1.625	−1.697	1.568	71
	(3.52)	(5.015)	(4.444)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	1.402	−2.247	1.913	71
	(3.118)	(6.231)	(5.1)	
Change (%) in employment in Enterprises, 2014/2020	−1.062	−5.761	3.092	71
	(4.388)	(13.324)	(7.812)	
Change (%) in employment in Enterprises, 2014/2019	−1.743	−5.178	3.198	71
	(5.764)	(12.241)	(8.094)	
Change (%) in employment in Local units, 2014/2020	1.055	−2.832	0.189	113
	(2.513)	(5.935)	(1.902)	
Change (%) in employment in Local units, 2014/2019	0.965	−1.004	0.08	113
	(2.47)	(4.16)	(1.642)	

Source: Eurostat, DG-Regio, 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 75 to maximum, uniform weighting; *Quadratic all* = quadratic functional form, bandwidth of 75 to maximum, uniform weighting; *Optimal bandwidth* = linear functional form, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

Table A 4 – Treatment effect of EU cohesion policy at the 90% cutoff (Fuzzy RDD)

EU expenditures as % of GDP as measure of treatment intensity

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	−2.464	7.499	7.494	80
	(4.003)	(6.458)	(7.193)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	−2.464	7.499	7.494	80
	(4.003)	(6.458)	(7.193)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	−24.525	51.588	−1.182	32
	(29.168)	(272.972)	(3.729)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	−1.944	−19.036	−12.618	70
	(8.516)	(146.709)	(32.428)	
Change in number of local units per 1,000 inhabitants, 2014/2020	7.445	3.856	−18.759	170
	(18.066)	(8.971)	(84.319)	
Change in number of local units per 1,000 inhabitants, 2014/2019	7.769	3.829	−7.263	170
	(18.07)	(8.738)	(30.074)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	−5.448	−38.615	−8.007	98
	(6.975)	(821.285)	(17.271)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	−5.625	−26.978	−6.563	98
	(7.445)	(581.88)	(13.606)	
Change (%) in employment in Enterprises, 2014/2020	−0.299	−65.197	10.446	98
	(2.164)	(1381.022)	(34.817)	
Change (%) in employment in Enterprises, 2014/2019	0.775	−71.116	−8.165	98
	(3.907)	(1524.62)	(22.849)	
Change (%) in employment in Local units, 2014/2020	11.926	8.125	−28.426	170
	(49.736)	(30.466)	(77.984)	
Change (%) in employment in Local units, 2014/2019	7.877	4.085	−16.151	170
	(45.85)	(28.064)	(56.391)	

Source: Eurostat, DG-Regio, 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

10.2. Appendix B: Additional robustness checks for sharp RDD (intention-to-treat effect)

Table B 1 – Sharp RDD (intention-to-treat effect) at the 75% cutoff

Subsample of EU member states before 2004

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	10.566	47.469	45.459	30
	(18.669)	(29.679)	(33.279)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	10.566	47.469	45.459	30
	(18.669)	(29.679)	(33.279)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	−6.033	109.337	−5.058	16
	(13.929)	(152.525)	(14.026)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	0.958	28.132	33.109	30
	(14.347)	(22.925)	(28.394)	
Change in number of local units per 1,000 inhabitants, 2014/2020	−3.500	−2.275	−11.481	60
	(4.583)	(7.626)	(11.149)	
Change in number of local units per 1,000 inhabitants, 2014/2019	1.828	2.297	−16.656	60
	(4.471)	(7.063)	(12.619)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	4.899	16.971	20.552	38
	(5.889)	(9.997)	(16.543)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	4.733	16.316*	20.724	38
	(5.756)	(9.952)	(15.821)	
Change (%) in employment in Local units, 2014/2020	4.197	−13.759	24.712	59
	(14.285)	(15.093)	(37.086)	
Change (%) in employment in Local units, 2014/2019	5.832	−8.837	11.561	59
	(14.733)	(12.423)	(21.072)	

Source: Eurostat, 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

Table B 2 – Sharp RDD (intention-to-treat effect) at the 90% cutoff

Subsample of EU member states before 2004

	Linear all	Quadratic all	Optimal bandwidth	N
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2020	8.068	−20.985**	−4.838	73
	(11.426)	(10.462)	(4.003)	
Cumulative number of enterprise births per 1,000 inhabitants, 2014–2019	8.068	−20.985**	−4.838	73
	(11.426)	(10.462)	(4.003)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2020	−5.690*	−11.309	−1.631	32
	(3.285)	(13.363)	(5.092)	
Cumulative number of enterprise deaths per 1,000 inhabitants, 2014–2019	−3.334	−16.558**	−17.258*	61
	(8.691)	(7.596)	(9.182)	
Change in number of local units per 1,000 inhabitants, 2014/2020	5.877**	4.704	10.738	158
	(2.635)	(3.915)	(7.816)	
Change in number of local units per 1,000 inhabitants, 2014/2019	6.324**	4.709	4.734	158
	(3.062)	(4.939)	(6.249)	
Change in number of enterprises per 1,000 inhabitants, 2014/2020	7.465**	−5.920	6.154	91
	(3.447)	(4.811)	(6.013)	
Change in number of enterprises per 1,000 inhabitants, 2014/2019	7.313**	−4.220	5.566	91
	(3.255)	(4.282)	(5.332)	
Change (%) in employment in Local units, 2014/2020	1.418	4.359	5.381	158
	(4.069)	(6.142)	(6.787)	
Change (%) in employment in Local units, 2014/2019	−4.096	−5.093	−6.941	158
	(5.223)	(8.033)	(10.564)	

Source: Eurostat, 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

Table B 3 – Sharp RDD (intention-to-treat effect) by education (75% cutoff)

	Below Median Education				Above Median Education			
	Linear all	Quadratic all	Optimal bandwidth	N	Linear all	Quadratic all	Optimal bandwidth	N
Change in number of local units per 1,000 inhabitants, 2014/2020	10.210	−2.279	−4.943	47	−4.462	−3.740	−2.992	67
	(9.935)	(9.561)	(7.507)		(5.172)	(7.646)	(10.2)	
Change in number of local units per 1,000 inhabitants, 2014/2019	14.537	1.348	−5.091	47	−2.361	−2.232	−2.326	67
	(10.232)	(10.771)	(9.535)		(4.94)	(6.841)	(10.207)	
Change (%) in employment in Local units, 2014/2020	40.605	11.865	4.203	47	−15.160	−3.468	16.977	66
	(39.335)	(41.27)	(13.114)		(10.856)	(16.079)	(24.524)	
Change (%) in employment in Local units, 2014/2019	41.965	21.335	3.121	47	−16.248	−0.718	16.072	66
	(38.615)	(40.237)	(5.688)		(10.808)	(15.555)	(22.336)	

Source: Eurostat, 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.

Table B 4 – Sharp RDD (intention-to-treat effect) by education (90% cutoff)

	Below Median Education				Above Median Education			
	Linear all	Quadratic all	Optimal bandwidth	N	Linear all	Quadratic all	Optimal bandwidth	N
Change in number of local units per 1,000 inhabitants, 2014/2020	10.210	−2.279	−4.943	47	−4.462	−3.740	−2.992	67
	(9.935)	(9.561)	(7.507)		(5.172)	(7.646)	(10.2)	
Change in number of local units per 1,000 inhabitants, 2014/2019	14.537	1.348	−5.091	47	−2.361	−2.232	−2.326	67
	(10.232)	(10.771)	(9.535)		(4.94)	(6.841)	(10.207)	
Change (%) in employment in Local units, 2014/2020	40.605	11.865	4.203	47	−15.160	−3.468	16.977	66
	(39.335)	(41.27)	(13.114)		(10.856)	(16.079)	(24.524)	
Change (%) in employment in Local units, 2014/2019	41.965	21.335	3.121	47	−16.248	−0.718	16.072	66
	(38.615)	(40.237)	(5.688)		(10.808)	(15.555)	(22.336)	

Source: Eurostat, WIFO-calculations.

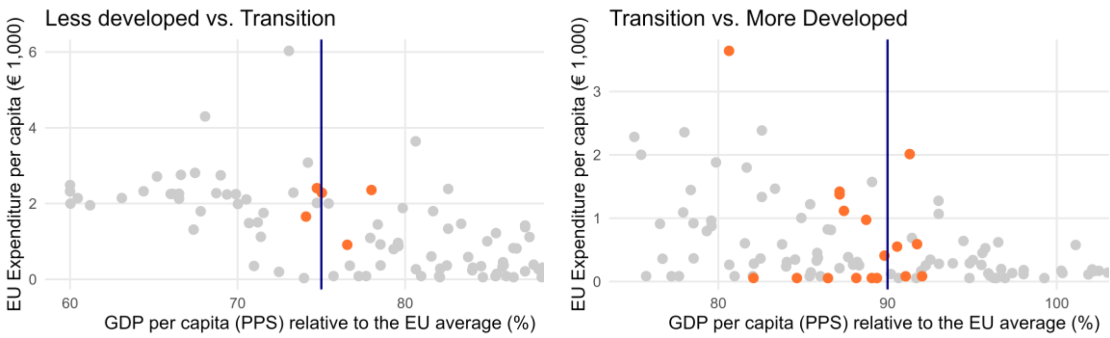
The table shows the regression coefficient of the interaction term between the running variable and the cutoff dummy for alternative specifications of equation (1). *Linear all* = linear functional form, bandwidth of 75 to maximum, uniform weighting; *Quadratic all* = quadratic functional form, bandwidth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

10.3. Appendix C: 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 categorised 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 categorised as “more developed” while others above the cutoff are in the “transition” region category.

Figure C 1 highlights these cases and shows that they are generally rare (especially around the 75% cutoff). In some instances, this may be 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 the results. We therefore estimated additional robustness checks using the categorisation 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 C 1 – Region categories vs. policy cutoffs



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

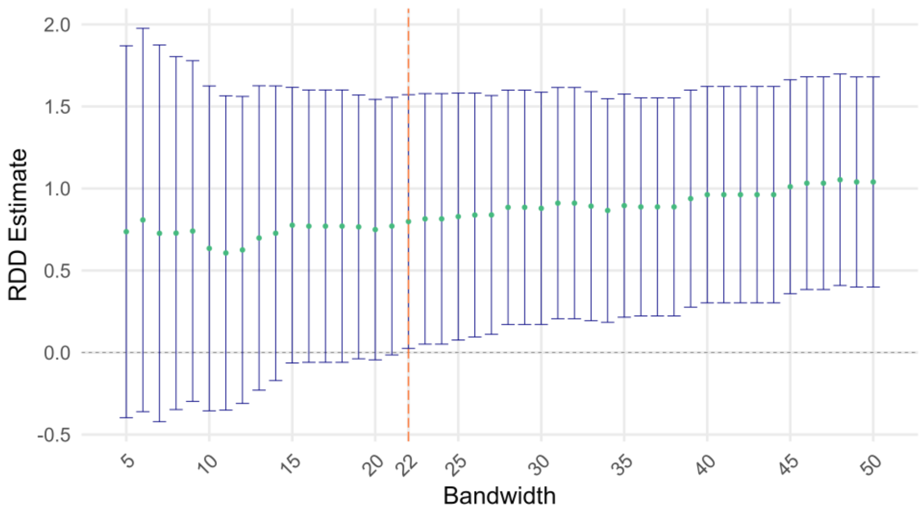
The figures only show regions within a +/- 15 percentage point bandwidth around the respective cutoff.

Table C 1 replicates the results of

Table 4 in the main text ([21]). 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 and again statistically insignificant, except for the inflexible "linear all" specification at the 75% cutoff. Furthermore, the results are again sensitive with regard to the bandwidth, as shown by Figure C 2 which replicates Figure 4 in the main text: only at relatively large bandwidths of more than +/- 22 percentage points will the linear first stage estimates turn significant at the 75% cutoff, while they are never statistically 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.

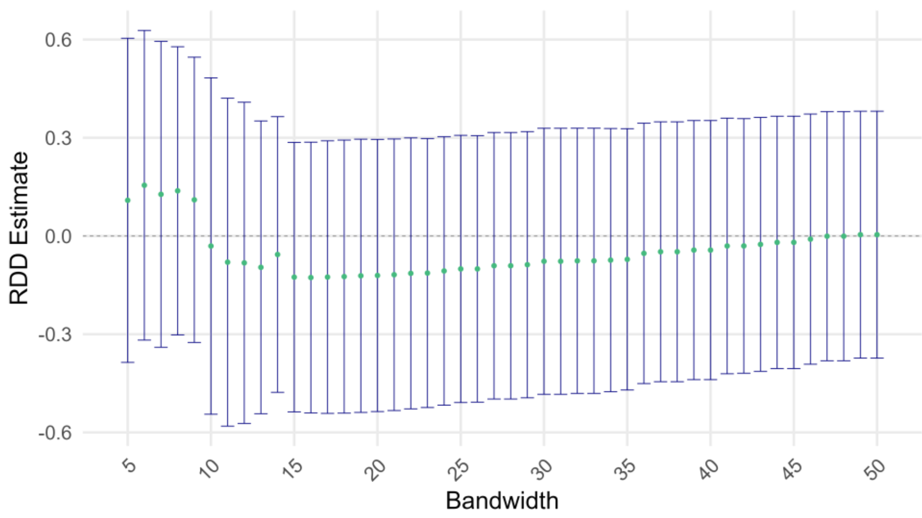
Figure C 2 – Simulation of tests for instrument relevance in dependence of the chosen bandwidth in the linear model, alternative treatment indicator

Cutoff 75%



([21]) The „optimal bandwidth" model is missing because the estimation routine used to calculate data-driven bandwidths does not allow regions below the cutoff that are untreated or regions above the cutoff that are treated.

Cutoff 90%



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

Table C 1 – First stage regressions of Fuzzy RDD design, alternative treatment group indicator

	75% cutoff		90% cutoff	
	Linear all	Quadratic all	Linear all	Quadratic all
EU expenditures per capita	1.040***	0.639	0.143	0.105
	(0.327)	(0.453)	(0.168)	(0.212)
EU expenditures in % of GDP	6.542***	3.651	0.884	0.387
	(2.321)	(3.360)	(1.118)	(1.455)
	Observations			
Left	73	73	48	48
Right	57	57	161	161

Source: DG-Regio, Eurostat, 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, data-driven bandwidth, triangular kernel weighting. ***, **, * signify statistical significance at the 1%, 5%, 10% level, values in brackets are (nearest neighbour) heteroscedasticity robust standard errors.