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Measuring the impact of Structural and Cohesion Funds using the Regression Discontinuity Design

FINAL TECHNICAL REPORT

WORK PACKAGE 14c – Task 1

Ex post evaluation of Cohesion Policy programmes 2007-2013, focusing on the European Regional Development Fund (ERDF) and the Cohesion Fund (CF)

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Abstract

The aim of this Report is the ex-post evaluation of Cohesion policy impact on economic growth in the EU-15 regions, which have benefited – to various extents – from financial assistance through two programming periods (from 1994 to 2006). The analysis is focused on both the average impact of SF (Structural and Cohesion funds) and the heterogeneity of the treatment intensity: it explores how the average effect of SF is affected by per capita intensity of SF and could influence regional development. We use a new regional dataset, which is fully coherent with Structural Funds Regulations 1994–1999 and 2000–2006, and the spatial grid defined by the EU15 regions at level 2 of the 2006 NUTS classification. We propose a new method for estimating the effects of intensity on growth, extending the RDD framework to the case of continuous treatment. The main result is that the positive and statistically significant impact of CP on regional growth is confirmed by the analysis.

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Final technical Report on Task 1

Measuring the impact of Structural and Cohesion Funds using the Regression Discontinuity Design

Table of Contents

EXECUTIVE SUMMARY 9

1. AIMS AND SCOPE 10
   1.1. Aim of the project 10
   1.2. Introduction and motivations 10
2. DATA 13
   2.1. 2.1 Novelty of data 13
   2.2. Some descriptive statistics and figures 14
3. ECONOMETRIC APPROACH 20
   3.1. 3.1 The impact of continuous treatment in a RDD framework 20
   3.2. The econometric model 22
4. RESULTS 24
   4.1. Main results 24
   4.2. Robustness analysis 32
5. CONCLUSIONS 34

REFERENCES 35

ANNEXES: FIGURES AND TABLES 37

Table of Figures

Figure 1 : Structural Funds intensity by NUTS2 regions 15

Figure 2 : Eligible areas and treated and non-treated regions 16

Figure 3 : Regional distribution of Structural Funds (Intensity = SF / Population) 17

Figure 4 : Kernel densities by treatment group 18

Figure 5: Relationship among the forcing variable, the GDP per capita growth rate and the SF Intensity (restricted sample) 25

Figure 6: GDP per capita growth rate and Structural Funds Intensity (full and restricted sample) 26

Figure 7: The effect of treatment intensity on regional growth (fully specified model) 31

Figure 8: The effect of treatment intensity on regional growth (fully specified IV model) 32

Table 1 : Descriptive statistics (mean) of NUTS2 regions by treatment status 19

Table 2: Continuous RDD parametric estimates: deviation from group means (Intensity = SF / Population) 27

Table 3: Continuous RDD parametric estimates: deviation from group means (Intensity = SF / GDP 1994) 28

1. EXECUTIVE SUMMARY

The aim of this Report is the ex-post evaluation of Cohesion policy impact on economic growth in the EU-15 regions, which have benefited – to various extents – from financial assistance through two programming periods (from 1994 to 2006). The analysis is focused on both the average impact of SF (structural and cohesion funds) and the heterogeneity of the treatment intensity: it explores how the average effect of SF is affected by per capita intensity of SF and could influence regional development. We use a new regional dataset, which is fully coherent with Structural Funds Regulations 1994–1999 and 2000–2006, and the spatial grid defined by the EU15 regions at level 2 of the 2006 NUTS classification. We propose a new method for estimating the effects of intensity on growth, extending the RDD framework to the case of continuous treatment.

The main result of the study is that the positive and statistically significant impact of SF on regional growth is confirmed. In the case of the fully specified RDD model on the period 1994-2007, the effect captured by the treatment dummy is high (0.7 percentage points in terms of annual GDP growth, when the intensity is on average), slightly lower that the estimate in Pellegrini et al. (2013), where the average impact is equal to 0.9 in the parametric approach. Considering the presence of potential endogeneity, and therefore using a Instrumental Variable approach, the impact has more than doubled. In term of share of GDP 1994, the impact is equal to 1.1%.

However, the positive impact of the intensity on Objective 1 NUTS 2 regions' growth is decreasing and it becomes statistically negligible after a certain threshold. Thus, there is evidence that NUTS 2 regions receiving lower SF intensity are much more sensitive to SF intensity changes than NUTS 2 regions receiving higher SF intensity levels and that after a certain intensity threshold additional transfers do not increase significantly the GDP.

A positive, statistically significant and decreasing impact of SF is registered even on different outcome variable, as GVA growth and employment rate growth, but not on labour productivity growth.

Finally, there are several elements that should be considered in order to fully evaluate our results. First of all, the outcome variable is the regional GDP growth rate. However, GDP is only one dimension on the target of EU regional policy, that is oriented to remove economic and social disparity across European regions. Therefore effects on GDP are important but cannot exhaust the purpose of the regional policy. Moreover, the decreasing of the marginal returns of transfers can be differentiated by target. For instance, the impact could be always positive in term of employment or social inequality. Therefore this analysis can give some suggestion on interregional allocation of UF, but cannot be the base of a new allocation of UF transfers among European regions.

1. AIMS AND SCOPE

1.1. Aim of the project

The aim of the full project is the ex-post evaluation of Cohesion policy impact on economic growth in the EU-27 regions which have benefited – to various extents – from financial assistance through multiple programming periods, from 1994-1999 to 2007-2013. Object of Task 1 is the measurement of the UE transfers impact considering the heterogeneity in the intensity of transfers across European regions. The study explores how the average effect of SF is affected by per capita intensity of SF and influences regional GDP growth in the EU-15 regions in the 1994-2006 period. The proposed methodology is based on a counterfactual causal analysis and RDD (a method with high internal validity), that allows us to estimate the non-linear relationship between the intensity of EU regional transfers and per-capita growth. The proposed approach is new in the literature, and is based on the methodology for explaining effects heterogeneity presented in Becker, Egger and von Ehrlich (2013), modified for taking into account the intensity of the treatment.

1.2. Introduction and motivations

The aim of the study is to evaluate the impact of Structural and Cohesion Funds (SF) on regional economic growth in Europe The main difference of this study with the copious literature on this issue is twofold: first, we want to verify if the average impact of SF on regional growth also depends on the heterogeneity of transfers intensity, measured by the normalised amount of funds distributed in each region; second, the evaluation is based on the Regression Discontinuity Design (RDD), a quasi-experimental method with strong internal validity. It is the first paper that, to our knowledge, extends the framework of the RDD to the case of continuous treatment.

The effect of SF is strongly heterogeneous by country, region and time. There are several factors that could affect the impact of UF on different dimension on regional growth, and the use of counterfactual methods for policy evaluation often captures only average effect, without explaining differences in the outcome of EU regional policy among regions. The high heterogeneity of regional transfer intensity across regions, also within the same country, suggests that the intensity of allocated funds between regions is a primary source of variability of the impact. The intensity of SF transfers is defined as the amount of EU transfers per inhabitant or as the share of regional GDP at the beginning of the period. For instance, in the period 1994-2006 the region of North-Holland received an annual average per capita transfer close to €9, whereas the Região Autónoma dos Açores (PT) almost 85 time more (€773). Limiting the analysis to the regions with Objective 1 (Ob. 1) status during the period 1994-2006, and excluding those of Sweden and Finland, inserted in the Ob. 1 as under populated areas, the region with the least amount of per capita transfers was the Flevoland, also in Holland, with per capita annual funds amounting to €67.40, eleven times lower than the maximum. The differences in the intensity of transfers reflect the choice to allocate more resources to those regions that are particularly in need, to sustains areas with economic and social distress, measured with specific indicators, and finally to maintain some qualitative judgment by EU and individual Members. It is therefore useful to check whether the greater intensity of aid is reflected in improved economic performance.

The relationship between the aid intensity and the impact of SF is not known. Economists and policy makers ignore whether this relationship is linear, that is, if increasing the SF transfers would proportionally increase the impact on economic growth, or if it takes some other form. In other words, we do not know if the marginal efficiency of transfers, using economic jargon, is constant or in some parts of this relationship it is increasing or decreasing. Several arguments can justify the presence of a non linearity in the dose-response function of the SF transfers. Clearly, the assumption of diminishing returns to investment (and to subsidised investments) implies that a larger number of investment projects carried out would be associated with a lower return to investments (or transfers). In this case, after a determined level of SF transfers no additional (or even lower) per capita income growth effects would be generated (Becker et al., 2012). However, the effect of diminishing returns can be different across the least developed European regions, depending on the stage of development, the quality and quantity of social capital, and potential demand.

A different reason is the limited absorbing capacity of EUF transfers, especially in less developed countries and regions, which affects the making the most of the investments taking place in their territory. This would imply that some regions use EU transfers increasingly inefficiently as they receive more transfers. Several authors attribute this effect to a lack of administrative capacity. In a recent paper, Rodríguez-Pose and Garcilazo (2015) note that the European Commission (EC) adopted the view that poor institutions can undermine efforts to achieve greater economic cohesion and hinder the effectiveness of regional development strategies, as stated in the EC's Fifth Cohesion Report. Finally, a large amount of SF can be used as a substitute, and not as a complement, of national or regional funds, decreasing the total impact of SF to regional growth.

Becker et al. (2012) suggest a similar explanation for a minimum necessary level of regional transfers which is based on the big-push or poverty-trap theory of development, which states that transfers (or aid) have to exceed a certain threshold in order to become effective. For instance, this would be the case if the marginal product of capital were extremely low at too small levels of infrastructure or human capital.

Although the literature on the impact evaluation of the SF is very wide (for a recent review see Pellegrini et al., 2013), only a few papers evaluate the effects of transfer intensity. In particular, we know of two: Mohl and Hagen (2010), using the method of 'generalised propensity score' (GPS), shows that SF payments "have a positive, but not statistically significant, impact on EU regions' growth rates"; Becker et al. (2012), using again the GPS but applying it to NUTS3 regions, estimate the relationship between the treatment intensity of EU regional transfers and *per capita* growth for the two programming periods 1994–1999 and 2000–2006. They find that, overall, EU transfers enable faster growth in the recipient regions as intended, but in 36% of the recipient regions the transfer intensity exceeds the aggregate efficiency maximising level and in 18% of the regions a reduction of transfers would not even reduce their growth.

From a methodological point of view, both papers use the GPS approach, a non-parametric method to estimate treatment effects conditional on observable determinants of treatment intensity. The GPS is one of the methods proposed in the literature to address the problem of a continuous treatment. In this case the policy mechanism can be away from an experimental data framework because of the presence of multiple non random selection processes, related not only to the participation decision but also to the treatment level assignment. In presence of continuous treatment the selection bias problem cannot be tackled using the usual estimation method developed for the binary treatment case. GPS is the main econometric technique for policy evaluation in presence of continuous treatment, as it should be able to correct for selection bias into different levels of treatment intensity by comparing units that are similar in terms of their observable characteristics. The literature proposes few matching estimators for continuous treatment. The main approaches are based mostly on two methods: the generalisation of the propensity score approach in a regression contest (Hirano and Imbens 2004; Imai and Van Dijk, 2004), that is used by Mohl and Hagen (2010) and Becker et al. (2012), and the use of matching method with doses (Behrman, Cheng and Todd, 2004; Cattaneo, 2010). However, in both cases the analysis is limited to the treated group, and the comparison between treated and non-treated units is absent. Moreover, there is not an explicit concern on the selection process related to the treatment level assignment. A different two step matching approach to estimate the causal treatment effects as a function of the doses was proposed by Adorno, Bernini and Pellegrini (2007). The estimator matches treatment and comparison units that are similar in terms of their observable characteristics in both the selection processes (the participation decision and the treatment level assignment).

However, all the estimators based on the matching approach suffer the strong heterogeneity of regions, which is hardly captured by the observed covariates. Moreover, none of these papers have properly exploited the source of local randomness due to the sharp discontinuity in the assignment of different transfer intensity (75% of average GDP criterion). A different solution is proposed in our paper by using the continuous RDD, which allows for the first time a compelling evaluation strategy also in presence of a continuous treatment. The RD design was first introduced by Thistlethwaite and Campbell (1960), and the seminal paper by Hahn et al. (2001) provided the crucial identification results.[1] However, we will use a parametric approach, which is more restrictive than the non-parametric approach used in the GPS. On the contrary, the main assumption behind the GPS - selection into levels of the treatment is random conditional on a set of observable pre-treatment characteristics - is quite strong and the estimation of the dose-response function is parametric also in the GPS framework.

[1] See Imbens and Lemieux (2008) and Lee and Lemieux (2010) for a comprehensive review of the RD design.

2. DATA

2.1. Novelty of data

This study is based on a new, reliable and comparable dataset, stemming from several sources. The spatial grid used in our work is defined by 208 EU-27 regions at level 2 of the NUTS classification. We use the NUTS 2006 classification with adjustments to include data from 1994-1999 programming period:

− considering the 2003 and 2006 amendments to the NUTS 1999 classification, regions that, from 1999 to 2003 and/or from 2003 to 2006, experienced any "split" are included as in the NUTS 1999 classification (for Germany, Brandenburg; for Spain, Ceuta y Melilla; for Italy, Trentino-Alto Adige);

− NUTS-2 regions that, from 1999 to 2003 and/or from 2003 to 2006, experienced any "merge" are included as in the NUTS 2006 classification (for Germany, Sachsen-Anhalt);

− NUTS-2 regions that experienced, from 1999 to 2003 and/or from 2003 to 2006 any merge and split together, are considered as in the NUTS 2006 classification (some regions in Portugal and Finland);

− Denmark and Slovenia are presented with just one NUTS-2 (as in the NUTS 1999 and 2003 classifications).

Data on EU Structural and Cohesion Funds payments to Member States, broken down by programming period (1994-1999, 2000-2006, 2007-2013) and region per year, has been provided by the European Commission-DG REGIO. The originality and relevance of this dataset arises from its internal coherence (EU payments by operational programme per year) and extensiveness (it covers all the main funds, including the Cohesion Fund, the European Regional Development Fund (ERDF), the European Social Fund (ESF), the European Agricultural Guidance and Guarantee Fund (EAGGF); the Financial Instrument for Fisheries Guidance (FIFG)). Note that only data on SF are considered, without national co-financing and private funds.

This information was cross-checked and matched with the ESPON and ISMERI regional databases on Structural and Cohesion Fund spending, in order to define the volumes of payments from the EU to the individual NUTS-2 regions. For the programming period 1994-1999, as the totals per country are very similar to the totals produced by ESPON, we apply the ESPON NUTS-2 spending breakdown to define the volumes of payments from the EU to the individual NUTS-2 regions by Member State. For 2000 onwards, for each country, we adopt the regional weights of the ISMERI expenditure breakdown by NUTS2 regions and apply it to the European Regional Development Fund (ERDF) and Cohesion Fund data; for the European Social Fund (ESF), for each Member State we apply a different set of regional weights based on total population; for the European Agricultural Guidance and Guarantee Fund (EAGGF), and the Financial Instrument for Fisheries Guidance (FIFG), the regional weights are based on employment in agriculture.

For the empirical analysis we link these data with information on various regional characteristics from Eurostat and Cambridge Econometrics' Regional Databases. The data cover the years 1989 through 2011/2013.

As main outcome variables of interest we consider the average annual growth rate of per capita real GDP at NUTS-2 level. In order to use a unique source of information, data on regional GDP in volume are taken from Cambridge Econometrics' Regional Database.

We also consider alternative outcome variables and control variables at the level of NUTS-2 regions. Data on the real growth rate of GVA for the period 1994-2011 are available from Cambridge Econometrics. Information on Employment (6 sectors) and

Gross Fixed Capital Formation at NUTS2 regional level for the period 1989-2011 are taken from Cambridge Econometrics (consistent with Eurostat data, but more complete). We also employ information on the percentage of 25-64 year-olds with tertiary education from Eurostat (European Union Labour Force Survey) for the period 2000-2013, as well as data on population (total and the share of population aged 65 and over) and population density.

Cambridge Econometrics and the regional database of Eurostat were the main source of other pre-treatment covariates used in the analysis: employment rate, 15-64; productivity (GVA per hour worked); share of employment in service sector; and share of population over 65.

As in Pellegrini et al. (2013), we exclude from analysis four NUTS 2 regions whose level of *per capita* GDP in the period 1988–1990 (i.e., the reference period for the determination of Ob. 1 eligibility by the European Commission) was above 75 per cent of EU average, but were included in Ob. 1 for 'political reasons': Prov. Hainaut (BE), Corse (FR), Molise (IT), Lisboa (PT). Moreover, two regions (Aragón in Spain and Dytiki Makedonia in Greece) were clear outliers and were dropped from the sample.[2] Therefore, our final dataset consists of 202 regions, 53 "treated" and 149 "non-treated".

In line with the RDD approach, we selected a restricted sample, which includes the regions closest to the discontinuity. In order to still maintain a sufficient number of degrees of freedom, we have eliminated the lowest quarter for treated regions (in terms of initial level of per capita GDP) and the upper quarter for the non-treated regions. The restricted sample is then equal to 152 regions, 40 "treated" and 112 "non-treated". This smaller sample will be used for the main part of the analysis.

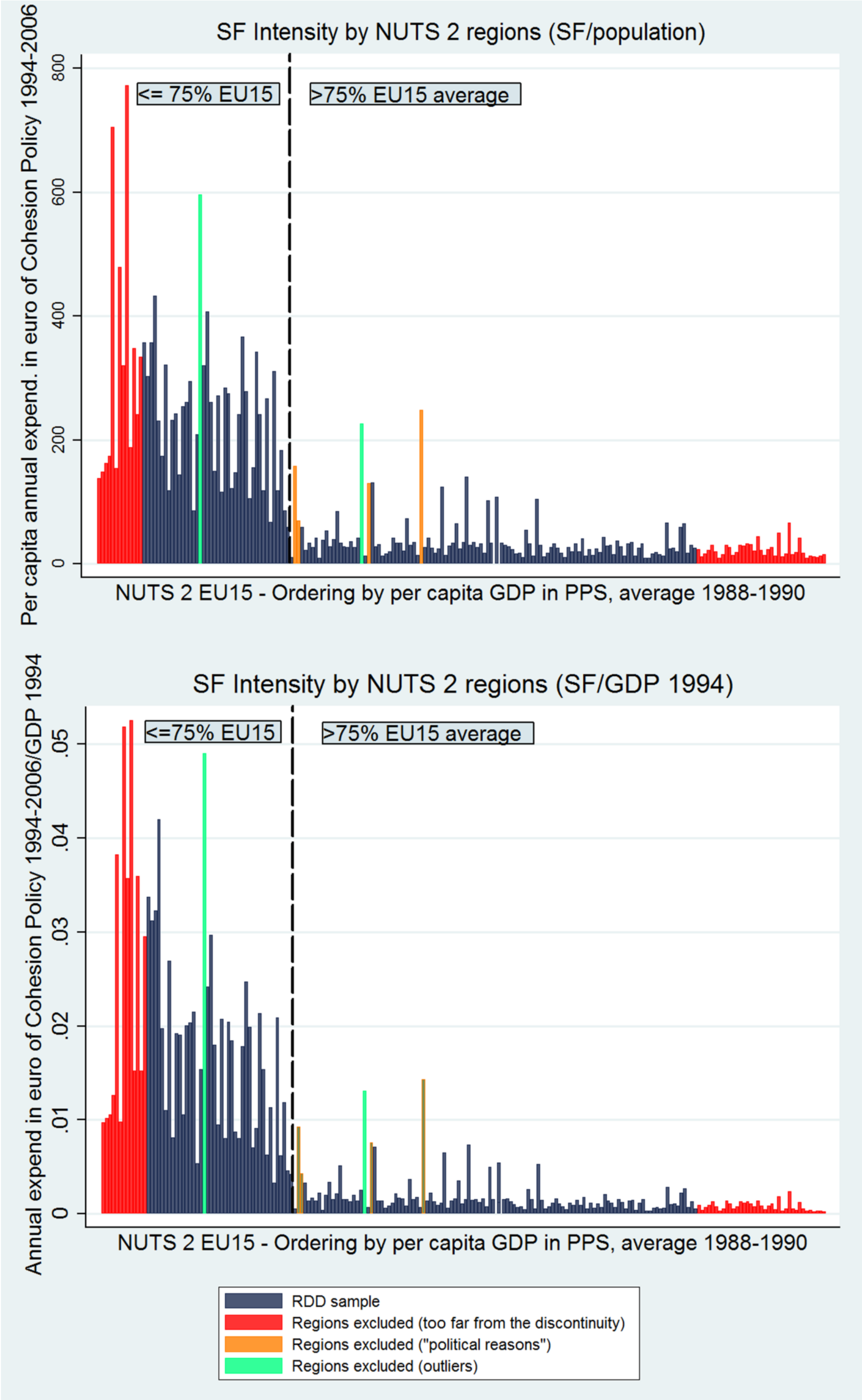
An important question is the normalisation of the EU regional expenditure. A normalisation is needed: The method used by the Commission in the allocation of resources for each member-state is based on a financial allocation per inhabitant per year, to be applied to the population living in the eligible regions (Barbieri and Pellegrini, 1999). From the above, the average population by region seems the "natural" normalisation variable. However, in the literature, the beginning-of period GDP has been used (Mohl and Hagen, 2010; Becker et al., 2012). The reason is that this share is a clear minimum target of the impact of SF on the economy. From our point of view there is not a prevailing method, therefore we used both indicators in our analysis.

2.2. Some descriptive statistics and figures

In Figure 1 we present the distribution of SF intensity by region, sorted by the 1988-1990 per capita GDP (our forcing variable). The regions we excluded from our sample because of 'political reasons' are in orange. The two groups of treated and non-treated regions are clearly differentiated. We graph the SF intensity, defined as the total amount of Structural Funds (European, national, regional and private) in the period 1994-2006 by region, normalised both by population (the population in 1994) and by GDP (the level of GDP at constant prices in 1994).

[2] Aragón is in the non-treated group, while Dytiki Makedonia is in the treated one. The criterion for outliers is to have received funds above the average plus 2.5 times the standard deviation of the respective treatment group in the restricted sample (once excluded the lowest quarter for treated regions -in terms of initial level of per capita GDP- and the upper quarter for the non-treated regions; see below in the paper).

Figure 1 : Structural Funds intensity by NUTS2 regions



The figures show how the excluded regions in green are clearly outliers in their groups, and do not modify substantially the distribution of the variable in both cases. The line of discontinuity accurately identifies the two groups of treated and non-treated (sharp design). There are very few cases where the contribution of SF is close to zero. The normalisation affects moderately on the differences between the two groups. As expected, the variability of the intensity is slightly lower for the variable normalised with respect to the GDP, especially for the non-treated.

Figure 2 shows the geographical position of treated and non- treated regions in the EU: the standard core-periphery picture is clearly exhibited, being the treated region mostly in the periphery.

As the paper is focused on the intensity distribution among European regions, Figure 3 shows the geographical location of the regions with different deciles of treatment intensity (SF by population) in the EU. In this figure the core-periphery picture is less clear, indicating that in the determination of the SF regional intensity several factors were at work.

Figure 2 : Eligible areas and treated and non-treated regions

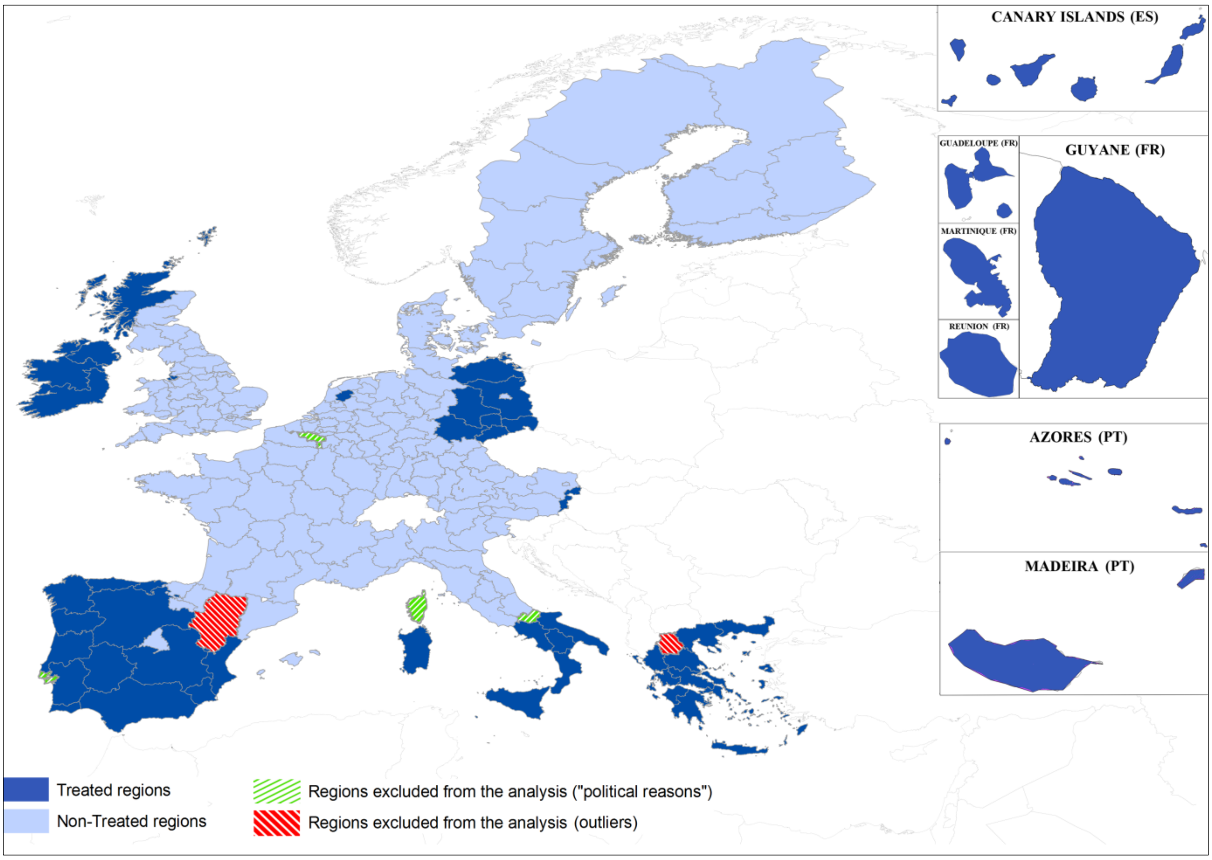
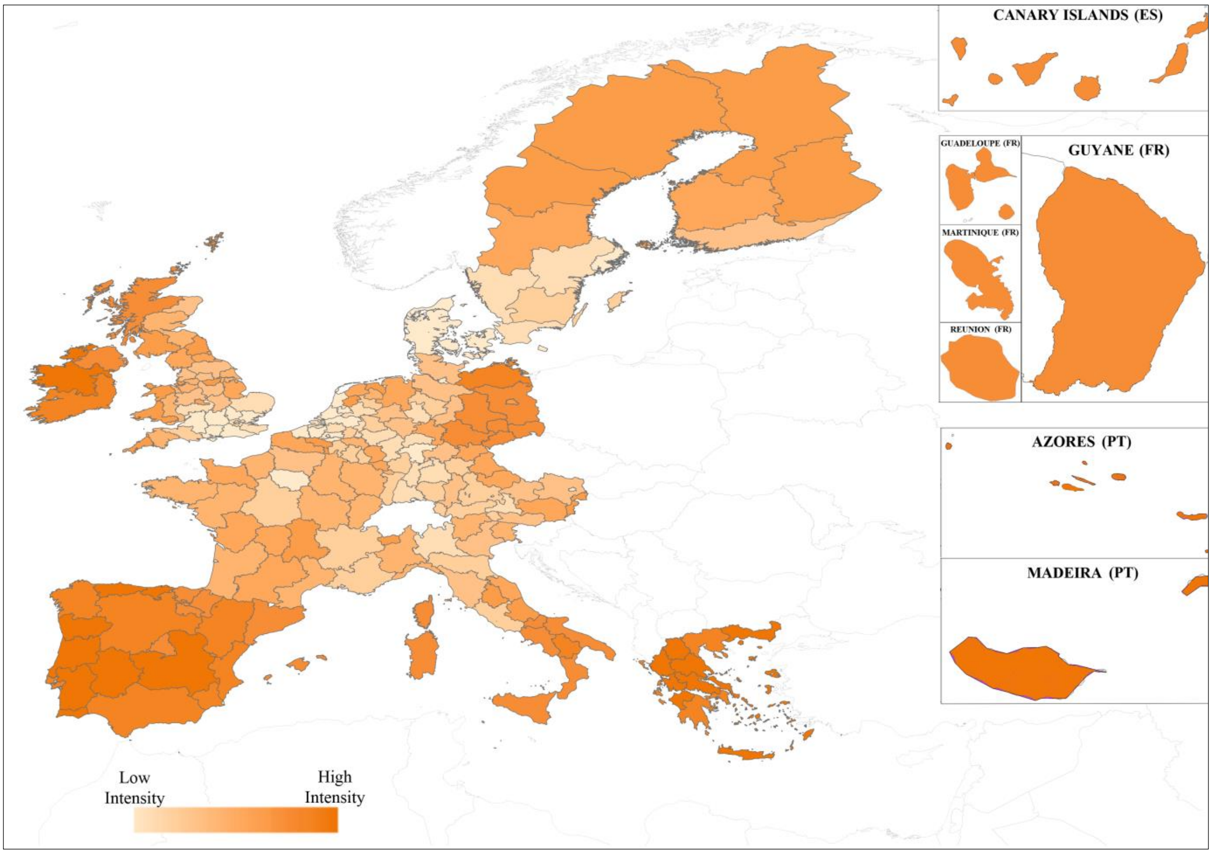


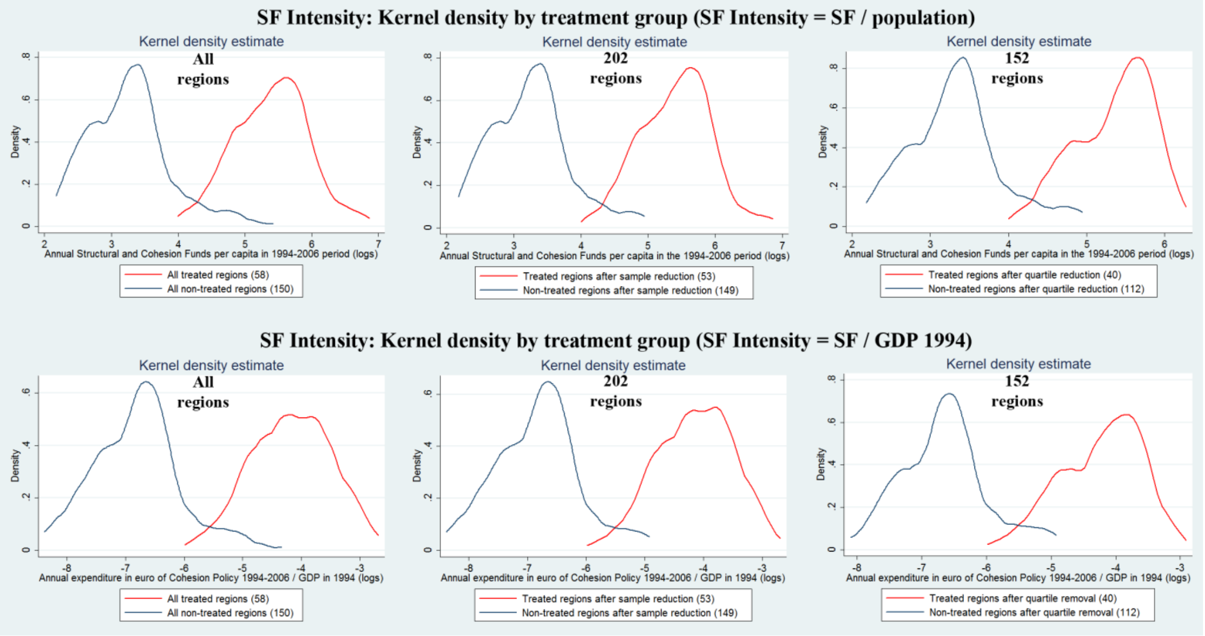
Figure 3 : Regional distribution of Structural Funds (Intensity = SF / Population)



How is the distribution of normalised SF intensity? This is an important question, because the possibility of having meaningful estimates depends on the variability of the normalised SF intensity and the shape of its distribution. In Figure 4 we present an estimation (using a standard kernel approach) of the distribution for treated and non-treated regions, using the two normalisations and the different samples. The intensity shows a large variability between the two groups, and the shape of the distributions shows typically a single mode and fat tails. As expected, the distribution is more concentrated when you reduce the size of the sample. There are no significant differences between the distributions of the two normalised intensities.[3] There is an area of overlap, which appears modest.

[3] This aspect is very important in our approach, because we will compare the treatment intensity between treated and non-treated regions in terms of differences of treatment by the average in their group. If the distribution of the treatment intensity is similar between treated and non-treated regions less of a difference in the mean level, it is possible to compare such intensity for all levels of treatment.

Figure 4 : Kernel densities by treatment group



In Table 1 we compare treated and non-treated regions with respect to different variables in the initial and final year of the research period. We also present the comparison in the large and in the restricted sample. Non-treated regions are generally smaller, but more populated than the treated ones. As expected, they are richer and also more productive. Still, the average *per capita* GDP growth is lower than that of the treated regions. As expected, in the restricted sample the differences are smaller than in the full sample. However, average values of the observed covariates in the restricted sample are in line with the average values in the whole sample.

Table 1 : Descriptive statistics (mean) of NUTS2 regions by treatment status

		Complete RDD sample (202 NUTS2)		Restricted RDD sample (152 NUTS2)	
		Treated (53 NUTS2)	Non-treated (149 NUTS2)	Treated (40 NUTS2)	Non-treated (112 NUTS2)
	GDP per capita compound growth rate (1994-2007)	2.33	2.03	2.43	2.08
	Area (km²)	19,630	14,775	20,191	16,502
	GDP per capita (EU 15 = 100, PPS) in 1988-1990	58.64	102.84	64.08	93.55
1994	GDP (millions of euro, constant prices 2005)	22,527	47,083	24,771	36,467
	Population (thousands of inhabitants)	1,578	1,893	1,719	1,657
	Population density (inhab./km²)	234	441	270	311
	Employment rate, 15-64	53.03	65.64	53.40	63.56
	Productivity (GVA per hour worked, constant prices 2005)	20.08	29.94	20.31	28.61
	Percentage in service sector	63.12	68.65	62.81	68.01
	Percentage population over 65	13.44	14.22	13.79	14.40
2006	GDP (millions of euro, constant prices 2005)	32,073	62,388	36,030	48,970
	Population (thousands of inhabitants)	1,648	1,994	1,819	1,746
	Population density (inhab./km²)	247	466	285	323
	Employment rate, 15-64	59.95	68.13	60.76	68.28
	Productivity (GVA per hour worked, constant prices 2005)	24.44	37.24	24.09	35.61
	Percentage in service sector	68.43	74.01	67.93	73.35
	Percentage population over 65	15.97	15.69	16.09	15.83

3. Econometric Approach

3.1. The impact of continuous treatment in a RDD framework

The key issue when evaluating public policies is to isolate their impact from other factors affecting the outcome under analysis. Our dataset on SF transfers presents a sharp discontinuity in the 1988-1990 per capita GDP and this allows using a quasi-experimental method deriving from a RD design approach. This enables us to identify the causal effect of transfers on regional growth performances. However, the standard RDD is developed for the case of binary treatment. Our idea is to extend the RDD in the case of continuous treatment, considering the intensity as a cause of the impact heterogeneity. When the treatment is continuous, treatment effects are affected by three components: the treatment level, the heterogeneity among the units and the stochastic component. Apart from the error term, the heterogeneity issue can be interpreted in two ways. First, for each level of treatment, the effects may vary among units: this is the traditional heterogeneity problem in the literature of programme evaluation with binary treatment, depending on the characteristics of each unit (covariate heterogeneity). This aspect is relevant for the precision and the unbiasedness of the estimation, but it is not considered in our analysis (see Becker et al., 2013). In this paper we focus on another source of heterogeneity, i.e. the differences in the effects across levels of treatment. This source of variability is handled by evaluating the average effect among units treated at different levels around the discontinuity. Assuming to have an infinite number of observations, a natural development of the treatment effects estimation in the continuous case is the difference between the average outcomes of the units treated at each level with the average outcomes of the untreated units around the cut-off. However, when the number of observations is finite and limited, the heterogeneity in covariate can dominate the heterogeneity in the level of treatment. One alternative is to combine designs and to assume that, after conditioning on covariates, treatment assignment (in differences from the mean for treated and not treated sample) is as-if randomised for those regions near the discontinuity. Therefore, our approach is a combined design, where we consider heterogeneity in RDD after conditioning in pre-treatment covariates. A similar approach, although adopted in a different framework, is presented in Keele et al. (2015). In this paper the problem is the presence of a strong self-selection between small neighbourhoods across treated and not treated areas. Therefore the paper proposes to combine designs and to assume that, after conditioning on the observable variables affecting treatment assignment and the SF intensity, treatment assignment and the differences from the mean in treatment are as-if randomised around the Ob. 1 assignment threshold.

A simple representation of the SF framework is the following: we assume two treatment status (S), a status with a high level of treatment (S_h) and a status with a low level of treatment (S_l). In each status the treatment varies in a continuous way around its mean, with the condition $E(S_h)>E(S_l)$. The level of treatment t is defined as the difference from the mean in each status: $t_h= S_h-E(S_h)$ and $t_l= S_l-E(S_l)$. Let us define $D=1$ if the region is in the status with high level of treatment and $D=0$ if the region is in the status with a low level of treatment.

The common potential outcome approach in a continuous treatment framework can be applied in our context: $y_i(T)$ represents the set of potential outcomes, for each region i, given a random sample indexed by i=1…N and T represents the continuous variable indicating the treatment level, changing from the classical binary definition, named t_i .Furthermore, the general observed outcome Y can be written as:

$$(1) \qquad y_i = d_i\, y_i\,(D=1, t_i) + (1-d_i)\, y_i\,(D=0, t_i)$$

where *D* is the dummy variable indicating the treatment status and $y_i(t_i)$ is the particular potential outcome for each status at the observed level t_i. The average treatment effect on the treated at the *t*-th level is estimated as:

$$(2) \qquad \square(T) = E[Y(D=1)-Y(D=0)|T=t]$$

The parameter □*(T)* can be defined as the average treatment level effect (ATLE) (see Adorno et al., 2007). However, our analysis is focused on the effect of t_i on y_i. In a RDD framework, the outcome y_i is a function of the treatment d_i, of the forcing variables x_i, and of the level of treatment t_i. Our estimate of the ATLE is local, in the sense that it applies in the neighbourhood of the threshold of treatment forcing variable x, for every given t_i.

We define the local average treatment level effect (LATLE) at the threshold x_0:

$$(3) \qquad LATLE(x_i = x_0, t_i) = LATLE(x_0, t_i) = E[y_{1i}\ |x_0, t_i] - E[y_{0i}\ |x_0, t_i]$$

where y_{1i} denotes the outcome with high treatment and y_{0i} the outcome with low treatment, and x_0 denotes the threshold values for the forcing variable. The expected value of y_i to changes in t_i given $x=x_0$ is the dose-response function (DRF) of y_i to t_i at the threshold:

$$(4) \qquad y_i = DRF(t_i|x= x_0) = E[y_i\ |x_0, t_i]$$

In our case, the DRF relates each value of the SF intensity to the GDP growth rate from 1994 to 2006. The estimation of the LATLE and the DRF in a RDD framework requires 3 different identifying assumptions[4]:

A1. Continuity of outcomes at threshold: *$E(y_{1i})$ and $E(y_{0i})$ are continuous at x_0*

This is the standard identifying assumption in the RDD framework: every jump at the threshold must be attributed only to the forcing variable.

A2. Continuity of treatment intensity at the threshold: *The variable t_i is continuous at x_0*

Assumption A2 allows identifying the effect of the treatment, based on the average treatment intensity, and the effect of the intensity of the treatment, measured as the difference from the mean, for the treated and the untreated regions. The average jump is attributed to the difference in the average intensity of treatment between treated and not treated regions at threshold.[5]

A3. Random Assignment of treatment intensity conditional on the forcing variable and the covariates at the threshold: *The variable t_i is uncorrelated with the error term in the outcome equation, conditional on x_i and covariates Z_i at the threshold*

The assumption states that the treatment intensity (measured as the difference from the mean), conditioned on the forcing variables and other covariates, is randomly distributed between treated and not treated regions. The important condition is that treated and untreated regions having the same level of treatment (in differences from the mean) are not different by some unobservable dimension. The condition is similar to the condition of

[4] These assumptions adapt the HLATE framework proposed by Becker et al. (2013) to the case of continuous treatment.

[5] The plot of the treatment intensity distribution in Figure 6 in the next section shows us that assumption A2 is satisfied in our data.

weak unconfoundedness (CIA) in a GPS framework (Hirano and Imbens, 2004) but it is circumscribed around the threshold.[6]

3.2. The econometric model

In our context, this assumption states that, conditional on per capita GDP in the period 1988–1990, regions with different levels of treatment around the threshold do not differ in unobserved variables which are relevant for regional GDP growth. Even around the threshold, in case of a small sample, this condition can require some adjustment for baseline covariates. Therefore, the LATLE is estimated as:

$$(5) \qquad LATLE(x_0, t_i) = E[y_{1i} \,|x_0, t_{i,,} Z_i] - E[y_{0i} \,|x_0, t_{i,} Z_i]$$

where $Z_{i\ i}$ is a set of baseline covariates. We assume that $Z_{i\ i}$ captures the characteristics relevant to the probability to receive a relative high or low treatment intensity. Therefore, after controlling for these observable characteristics, any remaining difference in treatment intensity t_i across regions is independent of the potential outcome y_i.

The same holds for the DRF:[7]

$$(6) \qquad DRF(t_i|x= x_0 ,Z_i) = E[y_i \,|x=x_0, t_{i,,} Z_i]$$

Now we define the parametric control function for identification of the LATLE. We start from the "classic" sharp RDD framework:

$$(7) \qquad GY = a + b_0(x) + g*D + b_1(x)*D$$

where GY is the growth rate of per capita GDP, x is the forcing variable (average per capita GDP in the 1988-1990 period) and D is the treatment dummy, equal to 1 when treated, while $b_0(.)$ and b_1 (.) are sufficiently smooth polynomial functions of x.

Now we assume that the impact g(.) of the treatment is heterogeneous, and depends on t, the relative intensity of treatment (expressed in difference from the mean):

$$(8) \qquad GY = a + b_0(x) + g(t)*D + b_1(x)*D$$

Using a polynomial approximation for the term $g(t)*D$ we have:

$$(9) \qquad GY = a + b_0(x) + g_0(t) + g_1D + g_2(t)*D + b_1(x)*D$$

where $g_0(.)$ and g_2 (.) are a sufficiently smooth polynomial functions of t.

In case of a large sample, the heterogeneity would not be a problem for the RDD. However, in our finite sample, we cannot exclude that differences in intensities reflect differences in sample characteristics also around the threshold. As such, we wish to combine identification strategies and assume that, after conditioning on covariates, treatment relative level is locally randomised for those regions close to the threshold. Thus, we propose a mixed design, using both RDD and conditioning on observables (Z):

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[6] For the use of CIA in a RDD framework see also Angrist and Rokkanen (2016)

[7] Essentially, for the correct identification of the DRF assumptions A1 and A3 are sufficient. Besides, it is possible to represent the DRF with respect to the absolute value of the intensity instead of the difference between the intensity and the intensity average of the corresponding treatment group.

$$(10) \quad GY = a + b_0(x) + g_0(t) + g_1D + g_2(t)*D + b_1(x)*D + h(Z)$$

Our approach can be explained in two different ways. The first explanation is that we are estimating the intensity effect around the "average treatment impact". Actually we exploit variation in intensity for treated and non-treated regions around the average treatment effect for both groups. If we define the "average or normal effects of treatment given covariates" (GY_n), which includes the discontinuity, as:

$$(11) \quad GY_n = a + b_0(x) + g_1D + b_1(x)*D + h(Z)$$

where a includes the average intensity effect when the treatment is low, and g_1 includes the difference in effect between the average low and high level of treatment.

The conditioned effect of intensity is given by the difference from the "average effect of the treatment given the covariates":

$$(12) \quad GY - GY_n = g_0(t) + g_2(t)*D$$

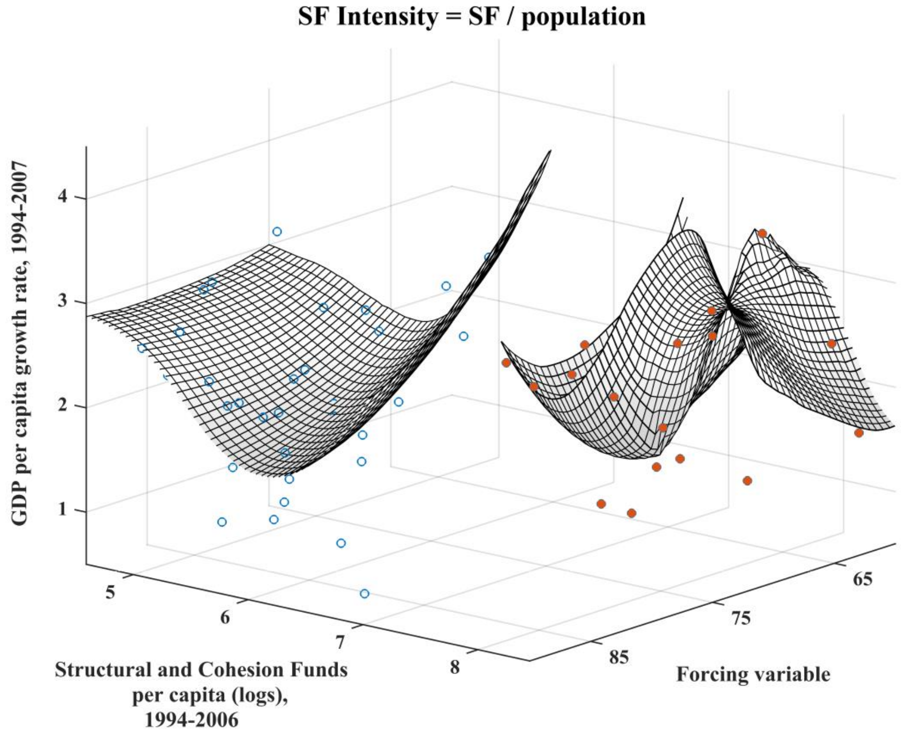
The second explanation is inside the Becker et al. (2013) framework. Intensity can be considered as one of the variables explaining the heterogeneity of the LATE. However, our approach is different in the use of covariates Z: we change Assumption 3 in Becker's paper (Random assignment of the interaction variable conditional on x_i), where the interaction variable (which, in our paper, is the relative level of treatment) is uncorrelated with the error term in the outcome equation, conditional on x_i (the forcing variable). In our framework the relative level of treatment t_i is uncorrelated with the error term conditional on x_i and the covariates Z.

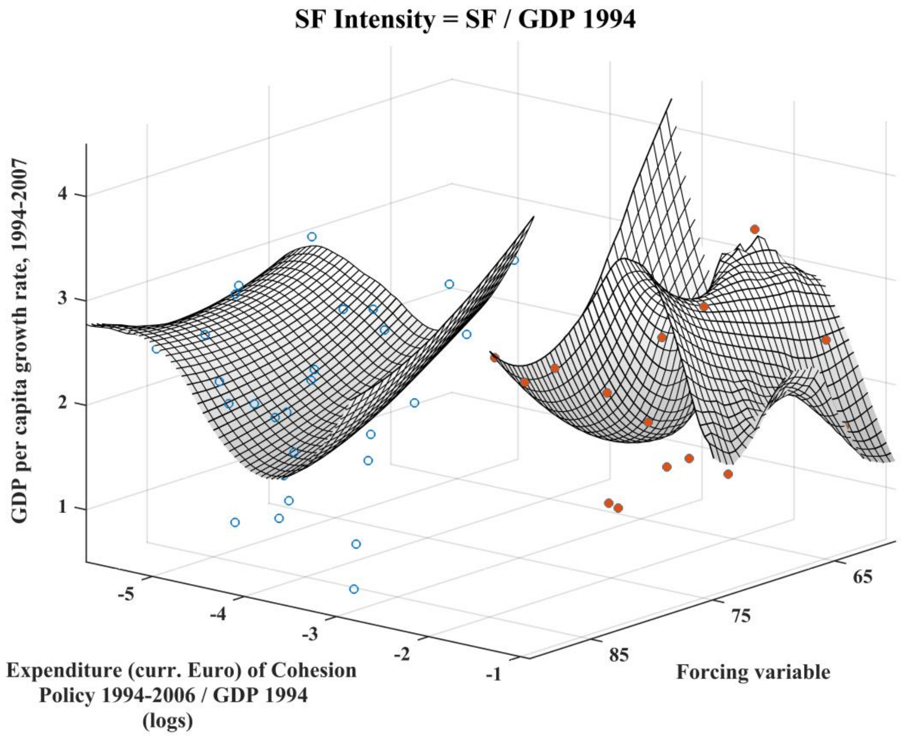
4. RESULTS

4.1. Main results

In a RDD analysis it is recommended to represent the relationship between the forcing variable and the outcome with a graph, in order to highlight also visually the presence of a discontinuity (Lee and Lemieux 2010). In our case the problem is more complex, because the variables of interest are 3, including also the intensity of the treatment. We then produced a three-dimensional graph, showing the relationship between the outcome variable (average annual compound growth rate of *per capita* real GDP for 1994–2007), the forcing variable (the level of *per capita* GDP in PPS, EU 15 = 100) by region, on either sides of the cut-off (75% of EU average GDP per head in PPS, average 1988–1990), and the intensity, using both the explained normalisations (Figure 5).

Figure 5: Relationship among the forcing variable, the GDP per capita growth rate and the SF Intensity (restricted sample)





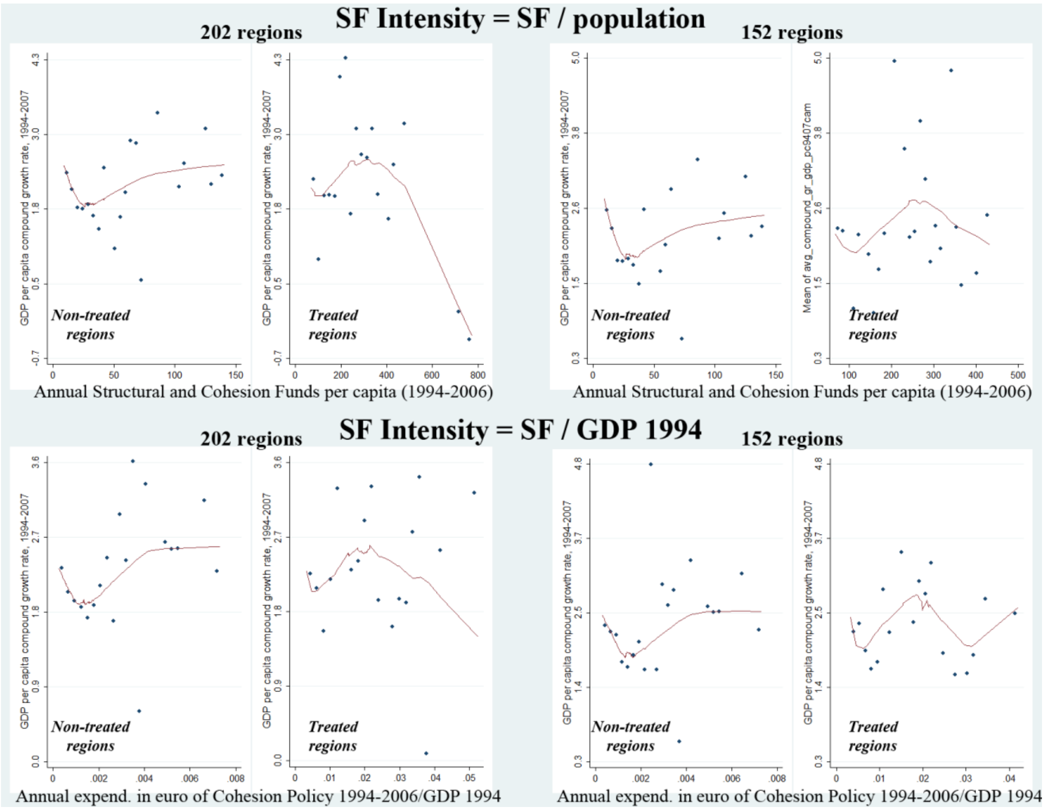
Notes: The upper and lower figures illustrate the relationship between GDP per capita growth rate (1994-2006), forcing variable and EU funds intensity. The solid (hollow) dots indicate regions that were considered (were not considered) Ob. 1 regions. The surfaces represent quadratic lowess functions (using a bi-square weight function and a bandwidth of 0.8) of the forcing variable and subsidy intensity. These functions are estimated on both sides of the threshold separately.

In Figure 5, the cut-off line sharply distinguishes between treated regions (i.e., Ob. 1) and non-treated regions. The surfaces represent quadratic lowess functions (using a bi-square weight function and a bandwidth of 0.8) of the natural log of the forcing variable and the SF transfers intensity. These functions are estimated on both sides of the threshold separately.

The graphs show the typical shape of the RDD. On average, Ob. 1 regions show higher growth rates than other EU 15 regions, and in the graph this is represented by a clear discontinuity. However, in this paper we are also interested in the relation between intensity and growth. The most interesting aspect of the figure is the concavity that is created in the surface along the intensity axis: the relation between intensity and growth is first steady and then growing among the non-treated regions; while, it increases to a maximum and then decreases for treated regions. This pattern is the same for the two normalisations. The figure then shows how the effect of the intensity on treated regions is not linear, decreasing after the internal maximum.

Disregarding the forcing variable, the relationship between the intensity of aid and growth can also be brought on a two-dimensional plane. Figure 6 clearly shows the different patterns of this relation among treated and non-treated regions. While for the non-treated regions, which are thus on the left side, the effect is first constant and then increasing, among the treated, the curvature underlined before is clear only in the restricted sample. The extreme values out of the space bounded by the restricted sample appear outliers compared to the basic relationship. Probably this is due to the peculiarity of these regions, either very underpopulated or very poor, which might determine the poor effects on their growth. Besides, the relationship between population and intensity shows rather clearly a negative sign, suggesting that there has been a reward for the smallest regions (Figure A1 in the Appendix).

Figure 6: GDP per capita growth rate and Structural Funds Intensity (full and restricted sample)



Notes: Histogram-style conditional mean with 30 bins by Ob. 1 status obtained using the Stata module “cmogram.ado”. For the interpolation line we used a local linear smoothing function.

Then, we move to the parametric estimation of the continuous RDD, using the model presented in section 3. Different order polynomials of the forcing variable can be introduced as regressors in the model, in order to allow different non-linear specifications of the relationship between the outcome and the forcing variable on both sides of the cut-off point. Therefore, the presence of a discontinuity in the relationship between GDP growth and SF transfers intensity at the threshold cannot be attributed to a missing non-linearity, but exclusively due to the Ob. 1 treatment. Lee and Lemieux (2010) argue that, in parametric regressions the choice of the polynomial order is as crucial as that of the bandwidth in the non-parametric approach. After few attempts, we decided to use a third-order polynomial for the forcing variable. We additionally conditioned the equations to some covariates, including surface area, population in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, hourly productivity in 1994 and employment rate among 15-64 years old in 1994.

The main result of the econometric analysis is that the positive and statistically significant impact of SF on regional growth is confirmed. Tables 2 and 3 present the estimates using the intensity expressed as differences from the means, for both definitions of intensity. In these equations, the treatment dummy coefficient also captures the effect of the average intensity.

Note that the treatment effect is positive and highly significant and that the intensity parameters are always jointly statistical significant at the 1% level, showing the importance of SF transfers intensity for GDP growth. We also interact the treatment dummy with the SF intensity, allowing a different effect of intensity for treated and not treated regions. In this case we have a fully specified model, which is our preferred specification.

Table 2: Continuous RDD parametric estimates: deviation from group means (Intensity = SF / Population)

Dependent variable: GDP per capita compound growth rate, 1994-2007						
	(1)	(2)	(3)	(4)	(5)	(5 IV)
Dummy Treatment (D)	0.083	0.504	0.709	0.402	0.699	1.875
	(0.361)	(0.489)	(0.531)	(0.626)	(0.628)	(0.654)***
Intensity	-	-	0.0037	0.0070	-0.0087	-0.0037
			(0.0025)	(0.0028)**	(0.0057)	(0.176)
Intensity Squared	-	-	-	-0.00002	0.0007	0.0015
				(0.0002)	(0.0002)***	(0.0007)**
Intensity Cubic	-	-	-	-1.36e-07	-5.53e-06	-0.00002
				(1.13e-07)	(2.0e-06)***	(7.81e-06)*
Intensity*D	-	-	-	-	0.0151	0.0104
					(0.0061)**	(0.0202)
Intensity Squared*D	-	-	-	-	-0.0007	-0.0016
					(0.0002)***	(0.0007)**
Intensity Cubic*D	-	-	-	-	5.29e-06	0.00002

					(2.0e-06)***	(7.86e-06)*
Polynomial order forcing variable	1	3	3	3	3	3
Other covariates	1	1	1	1	1	1
Intensity parameters jointly stat. sign. (5% level)	-	-	0	0	1	1
R-squared	0.1239	0.1465	0.1834	0.2581	0.3293	/
Nb. of treated regions	40	40	40	40	40	40
Nb. of non-treated regions	112	112	112	112	112	112

Note: Heteroskedasticity-robust standard errors in parentheses. The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994.

***p<0.01, **p<0.05, *p<0.1.

Table 3: Continuous RDD parametric estimates: deviation from group means (Intensity = SF / GDP 1994)

Dependent variable: GDP per capita compound growth rate, 1994-2007

	(1)	(2)	(3)	(4)	(5)	(5 IV)
Dummy Treatment (D)	0.083	0.504	0.752	0.752	1.098	1.886
	(0.361)	(0.489)	(0.566)	(0.727)	(0.774)	(0.959)**
Intensity	-	-	33.799	32.194	-139.78	-216.12
			(25.654)	(33.785)	(120.64)	(313.94)
Intensity Squared	-	-	-	-5,906	237,570	417,470
				(3,089)*	(74,093)***	(236,404)*
Intensity Cubic	-	-	-	149,429	-3.41e+07	-6.77e+07
				(136,123)	(1.35e+07)**	(4.10e+07)*
Intensity*D	-	-	-	-	136.77	185.38
					(122.54)	(296.44)
Intensity Squared*D	-	-	-	-	-245,229	-432,482
					(73,676)***	(238,642)*
Intensity Cubic*D	-	-	-	-	3.44e+07	6.81e+07

					(1.35e+07)**	(4.11e+07)*
Polynomial order forcing variable	1	3	3	3	3	3
Other covariates	1	1	1	1	1	1
Intensity parameters jointly stat. sign. (5% level)	-	-	0	0	1	1
R-squared	0.1239	0.1465	0.1650	0.2472	0.3148	/
Nb. of treated regions	40	40	40	40	40	40
Nb. of non-treated regions	112	112	112	112	112	112

Note: Heteroskedasticity-robust standard errors in parentheses. The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994.

***p<0.01, **p<0.05, *p<0.1.

In the case of the fully specified model, the effect captured by the treatment dummy is high (+0.7 percentage points more in terms of annual GDP growth, when the intensity is on average); this is due to the strong difference in the average treatment between treated and not treated regions. In Pellegrini et al. (2013) the average impact is equal to +0.9 in the parametric approach, close to our estimate. In term of share of GDP 1994, the impact is equal to 1.1%.

However, such relationship is decreasing with respect to the SF transfers intensity. For example, the average annual per capita transfer in treated regions (restricted sample) is around 231 euro. If we increase of 15% (€34.50) the transfers, the impact is lower (0.5 percentage points).

A simple way to represent graphically our results is to draw the curve described by the intensity coefficients of our models.

Using the estimates from the fully specified model (eq. 10), Figure 7 shows the average dose-response function of the GDP per capita growth rate and the SF transfers intensity and the treatment effect function (the marginal effect of on unit of treatment, i.e. the first partial derivative of DRF) by Ob. 1 status, both for different level of treatment intensity (SF by population) and with the 90 % confidence bands. As we can see in Figure 7, the dependent variable is an increasing function of the SF intensity. The average GDP per capita growth rate is positive for each value of the SF intensity. For instance, a SF intensity of €150 leads to an average GDP per capita growth rate of 2.8%, and a SF intensity of €200 leads to an average GDP per capita growth rate of 3.2%. This implies that the average causal effect of increasing the SF intensity from €150 to €200 is 3.2-2.8 = 0.4 percentage points, i.e. a 33% increase in SF intensity brings about a 14% increase in GDP per capita growth rate for Ob. 1 NUTS 2 regions.

However, the positive impact of the intensity on Objective 1 NUTS 2 regions' growth is decreasing and it becomes statistically negligible after a certain threshold. Qualitatively similar results are found using the alternative SF intensity definition (SF/GDP 1994).

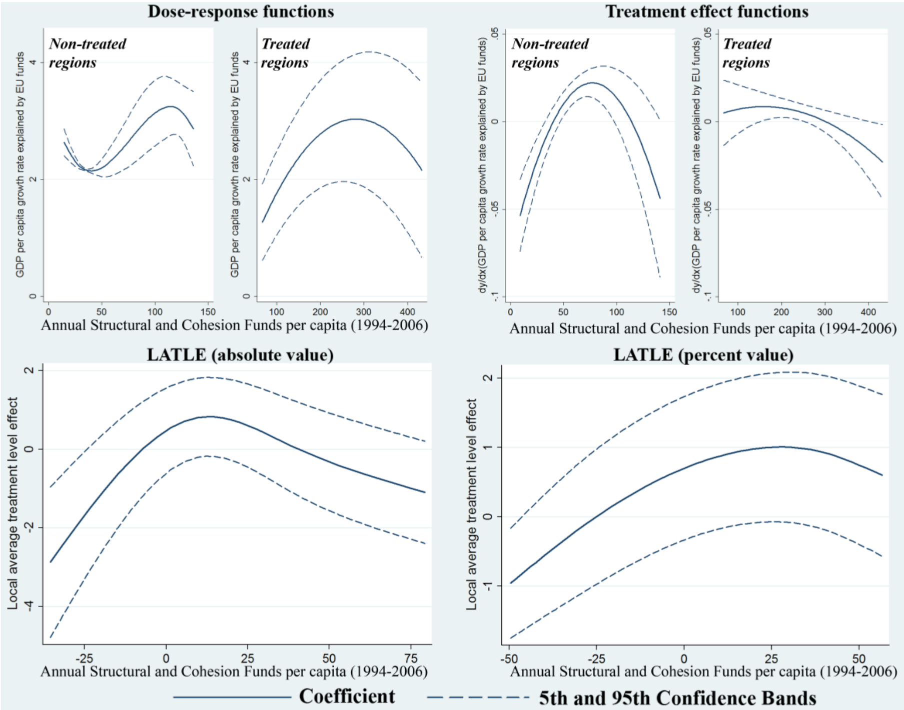
Thus, there is evidence that NUTS 2 regions receiving lower SF intensity are much more sensitive to SF intensity changes than NUTS 2 regions receiving higher SF intensity levels and that after a certain intensity threshold additional transfers do not increase GDP. Note that from Figure 7 we cannot exclude that the marginal effect of the treatment is constant and equal to zero after the maximum desirable SF intensity.

In Figure 7 we also represent the LATLE for both intensity normalisations. The impact is positive until around 0.2% of SF with respect to GDP in 1994 in terms of differences from the mean. However, the LATLE estimates are affected by the dimensional aspect of the comparison: €50 for non-treated regions represent an increase in SF transfers intensity of almost 1.5 times the mean, while for the treated regions such increase is much more limited (0.2 times the mean). Moreover, the dimensional aspect affects also the common support that is necessarily reduced.

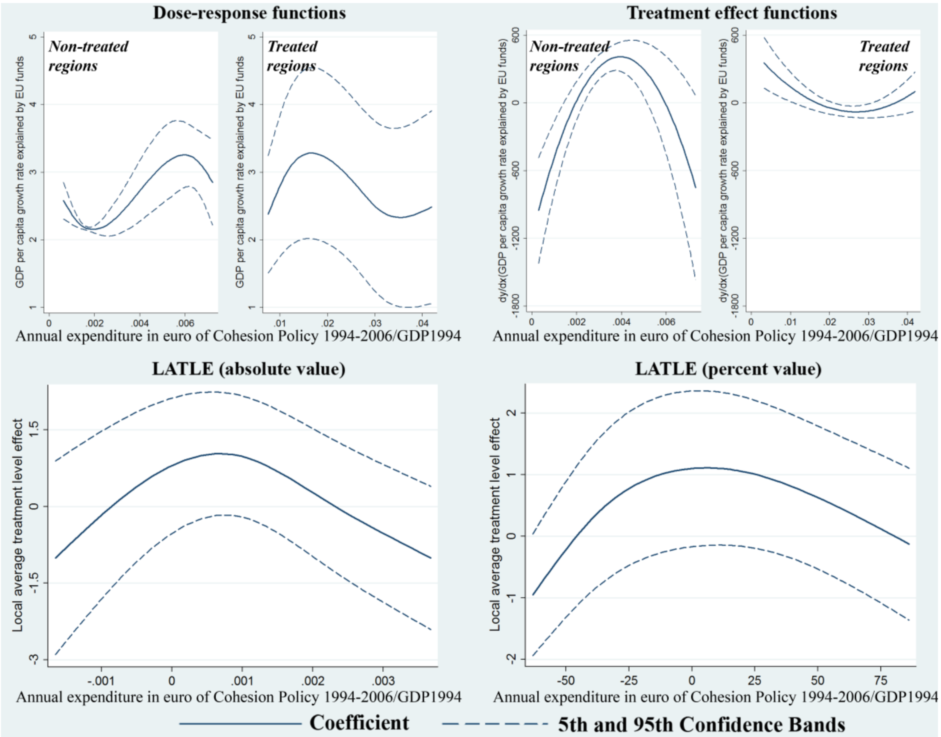
In a standard RDD, the treatment is clearly exogenous to the outcome. However, we cannot exclude that the intensity of the treatment is (partially) endogenous. For instance, regions using efficiently the SF and growing faster can receive more funds after a middle-period allocation revision. In presence of endogenous treatment intensity our estimates can be biased and the effect of intensity overestimated. Therefore we use an instrumental variables (IV) approach for attenuating this potential issue. As instruments we use a dummy for the cohesion fund countries, the forcing variable relative to the country level, the share of population relative to the country, and the share of employment in the agricultural sector, all covariates estimated in 1994. The results of the IV estimation are presented in the last column of Tables 2 and 3, and draw in Figures 8. The impact of SF is highly significant and more than double compared to the model OLS.

Figure 7: The effect of treatment intensity on regional growth (fully specified model)

SF Intensity = SF / population

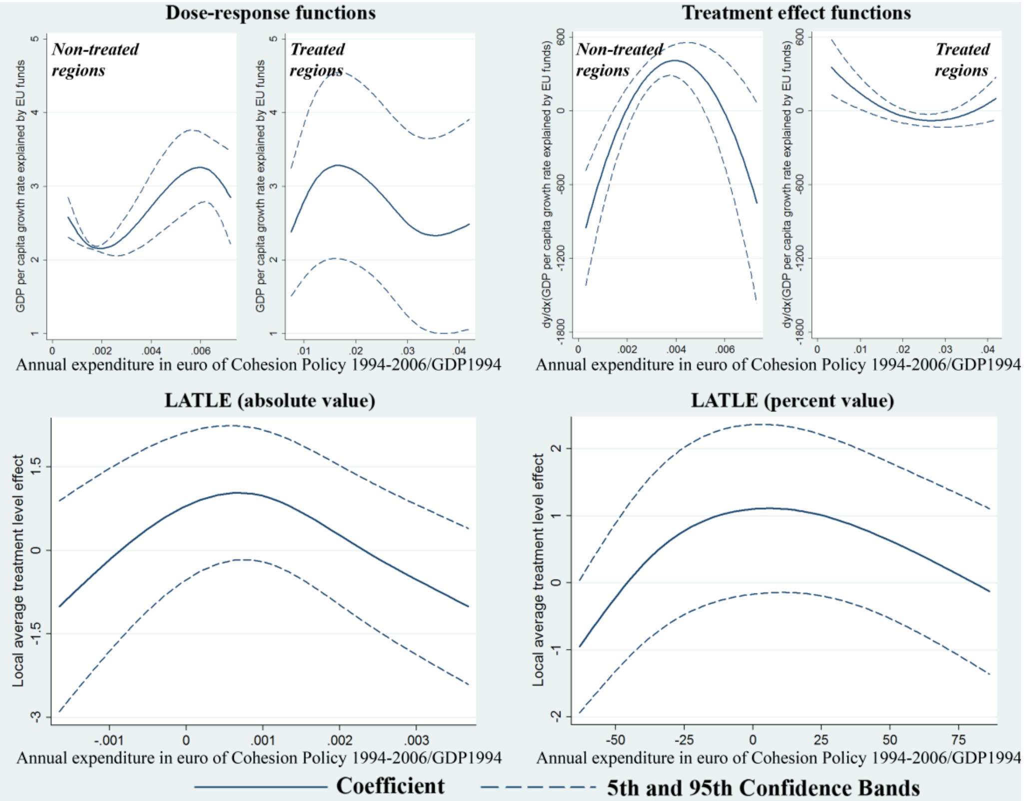


SF Intensity = SF / GDP 1994



Notes: (Left panel) Average dose-response function and 90% confidence bands by Ob. 1 status for the GDP per capita compound growth rate; (Right panel): Average treatment effect function and 90% confidence bands by Ob. 1 status for the GDP per capita compound growth rate; (Below panel): LATLE and 90% confidence bands limited to the common support between Ob. 1 and non-Ob.1 regions.

Figure 8: The effect of treatment intensity on regional growth (fully specified IV model)



Notes: (Left panel) Average dose-response function and 90% confidence bands by Ob. 1 status for the GDP per capita compound growth rate; (Right panel): Average treatment effect function and 90% confidence bands by Ob. 1 status for the GDP per capita compound growth rate.

4.2. Robustness analysis

Several robustness analyses, relative to the absence of sorting, the presence of other jumps in addition to that at 75% threshold and the presence of jumps at 75% threshold in other covariates in addition to the forcing variables are presented in Pellegrini et al. (2013) and are not reported here.

We consider here only 3 new analyses: the presence of spatial interference, the fuzzy design and the effect of the use of the whole period 1994-2006. The estimates are in the Appendix.

We check that the results do not depend on the use of the whole period 1994-2006 instead of splitting the periods in 1994-1999 and 2000-2006 (Tables A1-A2). After selecting a restricted sample (as in the main analysis, we have dropped the lowest quarter for treated regions in terms of initial level of per capita GDP and the upper quarter for the non-treated regions), we have estimated the parametric RDD with 5 different model specifications and the 2 different definitions of treatment intensity. In addition, we have also estimated the IV model for both definitions of treatment intensity. We find that the results are basically unchanged.

Spatial correlation can bias the estimation of our models. As data show the presence of a moderate spatial correlation across regional GDP growth rates, we re-estimate the models under the hypothesis that the errors are spatially correlated.[8] However, the results using the spatial error model and two different spatial weight matrices (Euclidean distance and rook contiguity) confirm the concave relationship between GDP growth and SF intensity (Tables A3-A4)

We also verify that the results do not depend on the choice of excluding from the analysis some outliers. This corresponds to evaluating fuzziness in the assignment rule considering 44 treated regions (and not only 40). The parametric fuzzy design estimation shows a coefficient of 1% instead of 0.7%.

[8] The specification of the spatial process for the regression error terms gives rise to a particular covariance structure, or pattern of spatial autocorrelation (Anselin, 2006).

5. CONCLUSIONS

The intensity of SF transfers is highly heterogeneous across regions, even within the same country. This paper focuses on both the average impact of SF (structural and cohesion funds) and the heterogeneity of the treatment intensity. We use a regional dataset, which is fully coherent with Structural Funds Regulations 1994–1999 and 2000–2006, and the spatial grid defined by the EU15 regions at level 2 of the 2006 NUTS classification. We propose a new method for estimating the effects of intensity on growth, extending the RDD framework to the case of continuous treatment.

The results confirm the positive effects of SF transfers on regional growth presented in Pellegrini et al. (2013). The findings of this evaluation show that regional policies have a role for stimulating regional growth and economic development. Even considering transfer heterogeneity, the results show a positive and statistically significant effect of SF on regional growth. The effects are in line with the results of other studies casted in a counterfactual framework.

Another important results is that the estimated conditional intensity-growth function is non linear, mostly concave and with a marginal efficiency of transfers null after a certain point. Therefore the analysis shows that the mechanism related to the allocation of UF transfers at national and EU level can be improved with a higher efficiency.

However, GDP is only one dimension on the target of EU regional policy, that is oriented to remove economic and social disparity across European regions. Therefore effects on GDP are important but cannot exhaust the purpose of the regional policy. Moreover, the decreasing of the marginal returns of transfers can be differentiated by target. For instance, the impact could be always positive in term of employment or social inequality. Therefore this analysis can give some suggestion on interregional allocation of UF, but cannot be the base of a new allocation of SF transfers among European regions.

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3. ANNEXES: FIGURES AND TABLES

Table A1: Continuous RDD parametric estimates: deviation from group means (Intensity = SF / Population) – 2 different Programming Periods

Dependent variable: GDP per capita compound growth rate 1994-2001 (for PP 1994-1999) and 2000-2007 (for PP 2000-2006)

	(1)	(2)	(3)	(4)	(5)	(5 IV)
Dummy Treatment (D)	0.209	0.546	0.741	0.716	0.863	1.820
	(0.361)	(0.447)	(0.513)	(0.652)	(0.656)	(1.714)
Intensity	-	-	0.0030	0.0053	-0.0063	-0.0369
			(0.0023)	(0.0025)**	(0.0051)	(0.0380)
Intensity Squared	-	-	-	5.88e-06	0.0003	0.0039
				(0.00001)	(0.0001)**	(0.0020)**
Intensity Cubic	-	-	-	-1.01e-07	-1.10e-06	-0.00003
				(7.04e-08)	(8.96e-07)	(0.00002)*
Intensity*D	-	-	-	-	0.0121	0.0547
					(0.0056)**	(0.0403)
Intensity Squared*D	-	-	-	-	-0.0003	-0.0037
					(0.0001)**	(0.0020)*
Intensity Cubic*D	-	-	-	-	9.94e-07	0.00003
					(8.99e-07)	(0.00002)
Polynomial order forcing variable	1	3	3	3	3	3
Other covariates	1	1	1	1	1	1
Intensity parameters jointly stat. sign. (5% level)	-	-	0	0	1	1
R-squared	0.2109	0.2213	0.2420	0.2668	0.2877	/
Nb. of treated regions	82	82	82	82	82	82
Nb. of non-treated regions	222	222	222	222	222	222

Note: Clustered standard errors at the NUTS2 level in parentheses. The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994

***p<0.01, **p<0.05, *p<0.1.

Table A2: Continuous RDD parametric estimates: deviation from group means (Intensity = SF / GDP 1994) – 2 different Programming Periods

Dependent variable: GDP per capita compound growth rate 1994-2001 (for PP 1994-1999) and 2000-2007 (for PP 2000-2006)

	(1)	(2)	(3)	(4)	(5)	(5 IV)
Dummy Treatment (D)	0.209	0.546	0.750	1.025	1.015	1.584
	(0.361)	(0.447)	(0.523)	(0.745)	(0.778)	(1.093)
Intensity	-	-	27.21	36.37	-164.08	-1,064.06
			(21.34)	(28.31)	(121.64)	(513.30)**
Intensity Squared	-	-	-	-3,202	115,910	849,790
				(2,087)	(50,960)**	(328,839)**
Intensity Cubic	-	-	-	29,195	-8,696,203	-1.04e+08
				(105,758)	(5,833,448)	(4.72e+07)**
Intensity*D	-	-	-	-	183.73	1,038.03
					(118.50)	(487.53)**
Intensity Squared*D	-	-	-	-	-119,918	-861,583
					(50,637)**	(328,348)***
Intensity Cubic*D	-	-	-	-	8,773,640	1.05e+08
					(5,832,965)	(4.72e+07)**
Polynomial order forcing variable	1	3	3	3	3	3
Other covariates	1	1	1	1	1	1
Intensity parameters jointly stat. sign. (5% level)	-	-	0	0	1	1
R-squared	0.2109	0.2213	0.2300	0.2633	0.2917	/
Nb. of treated regions	82	82	82	82	82	82
Nb. of non-treated regions	222	222	222	222	222	222

Note: Clustered standard errors at the NUTS2 level in parentheses. The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994.

***p<0.01, **p<0.05, *p<0.1.

Table A3: Continuous RDD parametric estimates using the Spatial Error Model: deviation from group means (Intensity = SF / Population)

Dependent variable: GDP per capita compound growth rate, 1994-2007

	(1)	(2)	(3)	(4)
Dummy Treatment (D)	0.166	0.468	0.400	0.669
	(0.608)	(0.658)	(0.589)	(0.576)
Intensity	0.0042	-0.0092	0.0070	-0.0088
	(0.0035)	(0.0049)*	(0.0027)***	(0.0053)*
Intensity Squared	-0.00002	0.0006	-0.00002	0.0007
	(0.00001)*	(0.0002)***	(0.00002)	(0.0002)***
Intensity Cubic	-6.76e-08	-4.72-06	-1.36e-07	-5.72e-06
	(1.16e-07)	(1.81e-06)***	(1.07e-07)	(1.93e-06)***
Intensity*D	-	0.0134	-	0.0153
		(0.0053)**		(0.0057)***
Intensity Squared*D	-	-0.0007	-	-0.0008
		(0.0002)***		(0.0002)***
Intensity Cubic*D	-	4.64e-06	-	5.58e-06
		(1.77e-06)***		(1.94e-06)***
ρ (rho)	3.342	2.968	-0.007	-0.083
	(0.937)***	(1.102)***	(0.132)	(0.133)
Spatial Matrix	Euclidean	Euclidean	Rook	Rook
Polynomial order forcing variable	3	3	3	3
Other covariates	1	1	1	1
Intensity parameters jointly stat. sign. (5% level)	0	1	1	1
Nb. of treated regions	40	40	40	40
Nb. of non-treated regions	112	112	112	112

Note: Heteroskedasticity-robust standard errors in parentheses. The polynomial functions are allowed to have different parameters to the left and the right of the threshold. We implemented the Spatial Error Model using the Stata modules spmat.ado and spreg.ado (see Drukker et al., 2013). The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994.

***p<0.01, **p<0.05, *p<0.1.

Table A4: Continuous RDD parametric estimates using the Spatial Error Model: deviation from group means (Intensity = SF / GDP 1994)

Dependent variable: GDP per capita compound growth rate, 1994-2007				
	(1)	(2)	(3)	(4)
Dummy Treatment (D)	0.099	0.798	0.748	1.078
	(0.623)	(0.759)	(0.684)	(0.720)
Intensity	-20.55	-125.14	32.19	-141.55
	(34.17)	(102.41)	(31.83)	(112.71)
Intensity Squared	-5,447	199,609	-5,920	244,144
	(2,499)**	(66,194)***	(2,916)**	(69,375)***
Intensity Cubic	238,505	-2.74e+07	150,675	-3.55e+07
	(109,550)**	(1.06e+07)***	(128,477)	(1.27e+07)***
Intensity*D	-	99.28	-	139.22
		(100.98)		(114.35)
Intensity Squared*D	-	-207,390	-	-251,785
		(65,973)***		(68,999)***
Intensity Cubic*D	-	2.77e+07	-	3.57e+07
		(1.05e+07)***		(1.27e+07)***
ρ (rho)	4.536	3.153	-0.014	-0.025
	(1.397)***	(0.743)***	(0.135)	(0.152)
Spatial Matrix	Euclidean	Euclidean	Rook	Rook
Polynomial order forcing variable	3	3	3	3
Other covariates	1	1	1	1
Intensity parameters jointly stat. sign. (5% level)	0	1	1	1
Nb. of treated regions	40	40	40	40
Nb. of non-treated regions	112	112	112	112

Note: Heteroskedasticity-robust standard errors in parentheses. The polynomial functions are allowed to have different parameters to the left and the right of the threshold. We implemented the Spatial Error Model using the Stata modules spmat.ado and spreg.ado (see Drukker et al., 2013). The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994.

***p<0.01, **p<0.05, *p<0.1.

Table A.5: Continuous Fuzzy RDD parametric estimates: deviation from group means (Intensity = SF / Population)

Dependent variable: GDP per capita compound growth rate, 1994-2007						
	(1)	(2)	(3)	(4)	(5)	(5 IV)
Dummy Treatment (D)	0.195	0.772	0.883	0.625	0.985	
	(0.397)	(0.596)	(0.561)	(0.708)	(0.741)	
Intensity	-	-	0.0044	0.0073	-0.0088	
			(0.0023)*	(0.0026)***	(0.0052)*	
Intensity Squared	-	-	-	-0.00002	0.0007	
				(0.0001)*	(0.0002)***	
Intensity Cubic	-	-	-	-1.22e-07	-5.68e-06	
				(9.78e-08)	(2.0e-06)***	
Intensity*D	-	-	-	-	0.0158	
					(0.0055)***	
Intensity Squared*D	-	-	-	-	-0.0008	
					(0.0002)***	
Intensity Cubic*D	-	-	-	-	5.55e-06	
					(2.0e-06)***	
Polynomial order forcing variable	1	3	3	3	3	
Other covariates	1	1	1	1	1	
Intensity parameters jointly stat. sign. (5% level)	-	-	0	1	1	
R-squared	0.1139	0.1053	0.1561	0.2431	0.3051	
Nb. of treated regions	44	44	44	44	44	
Nb. of non-treated regions	112	112	112	112	112	

Note: Clustered standard errors at the Country level in parentheses. The polynomial functions are allowed to have different parameters to the left and the right of the threshold. The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994.

***p<0.01, **p<0.05, *p<0.1.

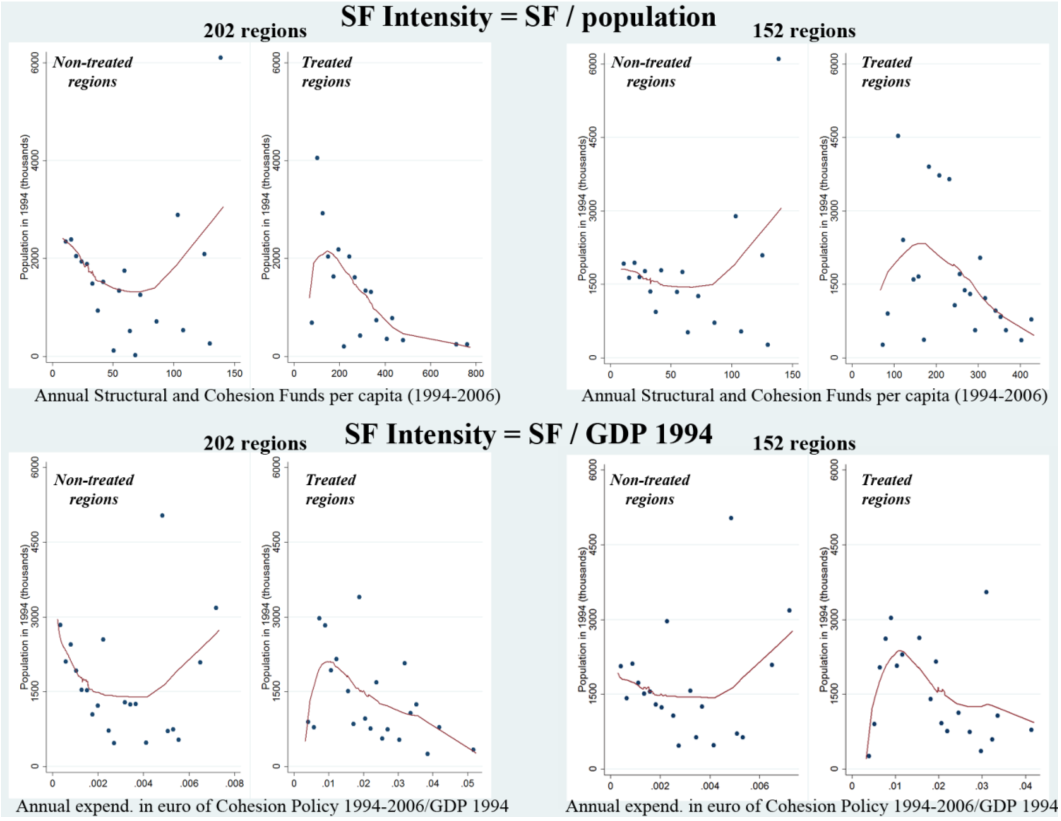
Table A.6: Continuous Fuzzy RDD parametric estimates: deviation from group means (Intensity = SF / GDP 1994)

Dependent variable: GDP per capita compound growth rate, 1994-2007						
	(1)	(2)	(3)	(4)	(5)	(5 IV)
Dummy Treatment (D)	0.195	0.772	1.034	1.089	1.500	
	(0.397)	(0.596)	(0.644)	(0.910)	(0.960)	
Intensity	-	-	49.784	52.140	-118.790	
			(27.362)*	(32.571)	(116.695)	
Intensity Squared	-	-	-	-6,787	242,600	
				(3,418)**	(69,274)***	
Intensity Cubic	-	-	-	152,843	-3.53e+07	
				(129,929)	(1.3e+07)***	
Intensity*D	-	-	-	-	143.676	
					(113.728)	
Intensity Squared*D	-	-	-	-	-251,285	
					(69,114)***	
Intensity Cubic*D	-	-	-	-	3.55e+07	
					(1.3e+07)***	
Polynomial order forcing variable	1	3	3	3	3	
Other covariates	1	1	1	1	1	
Intensity parameters jointly stat. sign. (5% level)	-	-	0	1	1	
R-squared	0.1139	0.1053	0.1313	0.2251	0.2736	
Nb. of treated regions	44	44	44	44	44	
Nb. of non-treated regions	112	112	112	112	112	

Note: Clustered standard errors at the Country level in parentheses. The polynomial functions are allowed to have different parameters to the left and the right of the threshold. The estimates are based on the 75% of the sample closest to the Ob. 1 assignment threshold (we exclude the lower quarter for the treated regions and the higher quarter for the non-treated regions). Other covariates include population in 1994, population density in 1994, percentage of over 65 in 1994, percentage in the service sector in 1994, productivity in 1994 and employment rate among 15-64 years old in 1994.

***p<0.01, **p<0.05, *p<0.1.

Fig. A1: Population and Structural Funds Intensity (full and restricted sample)



Notes: Histogram-style conditional mean with 30 bins by Ob. 1 status obtained using the Stata module "cmogram.ado". For the interpolation line we used a local linear smoothing function.

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