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Are we spending too much to grow? The case of Structural Funds

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Abstract: We evaluate whether the impact of EU Structural and Cohesion Funds (EUF) on Member States' regional economic growth depends on the intensity of treatment, measured by the normalised amount of funds distributed in each region. We use an original dataset that covers all the main sources of EUF and extend the regression discontinuity design to the case of continuous treatment. The results suggest an average positive effect on regional growth. The estimated conditional intensity-growth function is concave and presents a maximum value. Therefore, the exceeding funds could have been allocated to other lagging regions without reducing the effect on growth.

Keywords: EU Structural and Cohesion Funds; intensity of treatment; continuous regression discontinuity design

JEL codes: C21; H54; R11

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1. Introduction

The EU Structural and Cohesion Funds (EUF) represent one of the most important experiments of redistribution of resources within a continent. EUF aim to reduce disparities among EU Member

States and regions countering any centrifugal forces and helping to develop an area of almost free movement of goods and services. This policy has had strong supporters and detractors. Some have argued that such a policy was necessary to compensate the most backward regions for the negative effects that the reduction of barriers to entry would have on their economies. Conversely, this policy has sometimes been regarded as a vast waste of resources, with high costs in terms of efficiency and, consequently, in economic growth. The European centralisation of this policy, achieved using a common procedure throughout the EU, also has frequently been criticised as wasteful and inconsistent, reducing its popularity, particularly in the countries with the highest contributing shares. Indeed, such countries demanded a different approach, with the management of the policy entrusted to individual governments. Therefore, these positions have unsurprisingly stimulated many researchers to evaluate the policy's effectiveness. Nevertheless, this substantial amount of empirical studies has not brought to a general consensus on the effectiveness of EUF. Although the evaluation techniques have been refined over time, the lack of harmonised and common data over the long term along with the presence of many confounders has led to a proliferation of studies divided not only on the method and the data adopted but also, and above all, on their findings.

We evaluate the impact of EUF on Member States' regional economic growth from 1994 to 2006, verifying whether the uneven impact on regional growth also depends on the intensity of treatment. Our study contributes to the previous literature in two ways. First, we use an original dataset that covers all the main sources of EUF, and it is highly coherent (EU payments by operational programme per year and NUTS-2). The availability of this novel dataset allows us to carry out the analysis with increased precision than it was possible in the past. Second, the evaluation is based on an extension of the regression discontinuity design (RDD), a quasi-experimental method with strong internal validity and methodologically close to the HLATE approach developed by Becker et al. (2013). To our knowledge, this study is the first to expand the framework of the RDD to the case of continuous treatment.

The high heterogeneity of regional transfer intensity across regions and 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 EUF transfers is defined as the amount of transfers per inhabitant or as the share of regional GDP at the beginning of the period. For instance, from 1994 to 2006, the North-Holland region received an annual average per capita transfer close to €9 whereas the Região Autónoma dos Açores (PT) received almost 85 times more (€773). Limiting the analysis to the regions with Objective 1 (Ob. 1) status during the period from 1994 to 2006 and excluding sparsely populated regions that were classified as Ob. 1, the region with the least amount of per capita transfers was the Netherlands' Flevoland region, with per capita annual funds amounting to €67.40, eleven times lower than the maximum. The differences in the intensity of transfers reflect the decision to allocate more resources to those regions that are particularly needy, to sustain areas experiencing economic and social distress as measured by specific indicators and to maintain qualitative judgement by the EU and individual Member States. Therefore, determining whether the greater intensity of aid is reflected in improved economic performance is valuable.

The relationship between the aid intensity and the impact of EUF is unclear. Economists and policy-makers ignore whether the marginal efficiency of transfers is constant or increasing or decreasing in some parts of the relationship. If we assume that it is decreasing after a certain point, then the *maximum desirable level of transfers* is defined as the amount of aid per person after which the effect of EUF transfers on economic growth turns negligible. Several arguments can justify the presence of a concavity in the dose-response function of the EUF transfers. The assumption of diminishing returns to investment (and to subsidised investments) clearly implies that more investment projects would be associated with a lower return on investments or transfers. In this case, after a determined level of EUF 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 differ across the least developed European regions, depending on the stage of development, the quality and quantity of social capital, and the potential demand.

A different reason is the limited absorptive capacity of EUF transfers, particularly in less developed countries and regions, which affects the maximisation of the investments occurring in their territory. This reason would imply that some regions use EU transfers increasingly inefficiently as they receive more money. Several authors and the European Commission attribute this effect to a lack of administrative capacity and quality of institutions. The EU claims that poor institutions can undermine efforts to achieve greater economic cohesion and hinder the effectiveness of regional development strategies, as stated in the EU's Fifth Cohesion Report (2010). Rodríguez-Pose and Garcilazo (2015) demonstrate that poor institutional quality may be at the root of declining returns of regional development funds in Europe as the transfer intensity increases. Finally, a large amount of EUF can be used as a substitute, and not as a complement, to national or regional funds, decreasing the total impact of EUF on regional growth. Becker et al. (2012) suggest a similar explanation for a minimum necessary level of regional transfers that is based on the big-push or poverty-trap theory of development, which states that transfers or aid must exceed a certain threshold to become effective. For instance, this situation would apply if the marginal product of capital were extremely low at inadequate levels of infrastructure or human capital.

These arguments have direct implications for policy-makers. In a time of budget cuts, knowing that some regions are subsidised excessively can be helpful for a reallocation of transfers with positive effects on overall growth. Furthermore, this information may be highly important to recalibrate the system of transfers and maximise its efficiency.

Although the literature on the impact evaluation of the EUF is very broad (see, among others, Esposti and Bussoletti, 2008; Becker et al., 2010; Pellegrini et al., 2013; Dall'Erba and Fang, 2015; Giua, 2017), we know of only four papers that evaluate the effects of transfer intensity. Mohl and Hagen (2010) demonstrate that EUF payments "have a positive, but not statistically significant, impact on EU regions' growth rates". Conversely, Becker et al. (2012) estimate the relationship between the treatment intensity of EUF transfers and per capita growth for the programming periods 1994–1999 and 2000–2006 at NUTS-3 level. They find that these transfers enable faster overall growth in the recipient regions as intended, but the transfer intensity exceeds the aggregate efficiency maximising level in 36% of the recipient regions and a reduction of transfers would not even reduce growth in 18% of the regions. Becker et al. (2016) investigate the 2007-2013 programming period using an updated set of outcome variables, including education and innovation outcomes. Their findings are generally positive and suggest that regions generally tend to benefit from balanced funding of activities unless they are extremely specialised ex ante. From a methodological perspective, all these papers use "generalised propensity score" (GPS) matching (Hirano and Imbens 2004; Imai and Van Dijk, 2004), a non-parametric method to estimate treatment effects conditional on observable determinants of treatment intensity. Finally, Bouayad-Agha et al. (2013), using a spatial dynamic panel data analysis, find that EUF facilitated the convergence of Ob. 1 regions to average EU income levels, while the overall effect of EUF was negligible.

All the estimators based on the matching approach suffer from the strong heterogeneity of regions, which is hardly captured by the observed covariates. In this context, it is difficult to maintain the main assumption behind the GPS that selection into levels of the treatment is random, conditional on a set of observable pre-treatment characteristics.[1] 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. In fact, the majority of the funds accrue to Ob. 1 regions, i.e. to the less developed regions with per capita GDP (in purchasing power standards) below 75% of the EU average. Our study proposes an alternative solution which exploits the above discontinuity by using the continuous RDD, which for the first time allows a compelling evaluation strategy also in the presence of a continuous treatment. From a methodological point of view, our approach extends the

[1] Although the GPS approach 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, it does not have testable implications (Yang et al., 2016).

procedure proposed by Becker et al. (2013) for RDD with heterogeneous treatment effects to the case of continuous treatment. The results suggest that EUF had an average positive effect on regional growth. The estimated conditional intensity-growth function is concave and presents a maximum value. Therefore, the exceeding funds could have been allocated to other lagging regions without reducing the effect on growth.

The rest of the paper is organized as follows. In the next section we present details on the construction of data at the NUTS-2 regions level for the two programming periods 1994-1999 and 2000-2006. In Section 3 we discuss the econometric methodology applied for the identification of causal effects of the EU's regional transfers on economic growth. We present the results and interpret the findings in Section 4 and report the robustness checks in Section 5. The last section concludes with a summary of the most important findings.

2. Data and Sample

2.1. Data

This study is based on a new, reliable and comparable dataset, stemming from several sources. As we do not consider the accession countries in 2004 that did not receive transfers before 2004, the spatial grid used in our work is defined by 208 EU-15 regions at level 2 of the NUTS classification. We use the NUTS 2006 classification with adjustments to include data from the 1994-1999 programming period:

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

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

− NUTS-2 regions that experienced any merge and split together from 1999 to 2003 and/or from 2003 to 2006 are considered to be in the NUTS 2006 classification (3 Portuguese regions and 3 Finnish regions);

− Denmark is presented as a single NUTS-2 region (following the NUTS 1999 and 2003 classifications).

Data on EUF payments to Member States, broken down by programming period (1994-1999, 2000-2006) and region per year, have been provided by the European Commission-DG REGIO, and the final dataset is the result of a joint work involving the European Commission-DG REGIO together with external experts. The originality and relevance of this dataset arises from its internal coherence (EU payments by operational programme per year and NUTS-2) 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), and the Financial Instrument for Fisheries Guidance (FIFG)). Note that only data on EUF are considered, without national co-financing and private funds. However, national co-financing tends to be proportionate to EU funding and therefore may not substantially change the relative amount of funding distributed to different regions. The procedures adopted and the methodologies used for cleaning and the integration of different datasets are described in Roemisch (2016).

We link these data with information on various regional characteristics from Eurostat and Cambridge Econometrics' Regional Databases for our empirical analysis. The data cover the years 1994 through 2007.[2] We consider the compounded annual growth rate of per capita real GDP at NUTS-2 level as the main outcome variable of interest. Nevertheless, we also consider the

[2] We also collected data for the next programming period (2007-2013). However, we decided to exclude this period from our analysis because of the higher heterogeneity across regions, due to the entrance of new Member States in EU, having strong structural differences from the EU-15 countries and to the presence of the largest economic crisis in Europe since WWII, affecting the responses of each region to EUF.

compounded annual growth rate of real GVA, the employment growth rate and the labour productivity growth rate (real GVA per hour worked) as alternative outcome variables. To use a unique source of information, data are taken from Cambridge Econometrics' Regional Database (consistent with Eurostat data but more complete).

The regional databases of Cambridge Econometrics and Eurostat were the main sources of the pre-treatment covariates used in the analysis: the overall population, the population density, the share of the population over 65, the employment rate in those aged 15-64, labour productivity, and the share of employment in the service sector and in the agricultural sector.

2.2. Sample

Due to the limited changes to the Ob. 1 status assignment across regions between the two programming periods[3] analysed and to the significant time shift in payments, we decided to consider the entire 1994-2006 period in our main analysis. We adopt a fuzzy RDD as there was not perfect compliance with the Ob. 1 assignment rule. Indeed, four NUTS-2 regions had a 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) above 75 per cent of the EU average but were included in Ob. 1 for "political reasons":[4] Prov. Hainaut (BE), Corse (FR), Molise (IT), and Lisboa (PT). In the fuzzy RDD, the Ob. 1 assignment rule serves as an instrument for actual Ob. 1 treatment. Therefore, our full dataset consists of 208 regions — 58 "treated" and 150 "non-treated".

Consistent with the RDD approach, we selected a restricted sample including the regions closest to the discontinuity. To 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

[3] In the robustness section we test whether these changes of Ob.1 status (e.g., Corse in France and Lisboa in Portugal were phased out from Ob. 1 status in the 2000-2006 programming period) significantly affect our estimates.

[4] The procedure for funds allocation has not always been automatically determined and transparent. Political negotiations among Member States have often influenced the allocation of the EU budget. Consequently, in the different programming periods, a number of regions have been entitled to receive assistance within the Ob. 1 framework, even if they did not comply with the criterion set in the regulations (Pellegrini et al., 2013).

for the non-treated regions. Moreover, two regions (Aragón in Spain and Dytiki Makedonia in Greece) were clear outliers and were dropped from the restricted sample.[5] The restricted sample then includes 156 regions, where 44 were "treated" and 112 "non-treated". This smaller sample will be used for the main part of the analysis.[6]

The normalisation of the EU regional payments is an important question. A normalisation is needed as the European Commission allocates EUF for each Member State on the basis of a financial allocation per inhabitant per year, to be applied to the population living in the eligible regions (Barbieri and Pellegrini, 1999). From the preceding description, the average population by region at the beginning of the programming period seems the "natural" normalisation variable and we use it in the main analysis. However, as previous studies have used the beginning of period GDP (Mohl and Hagen, 2010; Becker et al., 2012) because this share is a clear minimum target of the impact of EUF on the economy, we adopt this alternative normalisation to check the robustness of the findings and report the results in the Appendix.

In Figure 1 we present the distribution of EUF intensity by region using both normalisations (the population in 1994 and the level of GDP at constant prices in 1994), sorted by the 1988-1990 per capita GDP (our forcing variable). The regions included in Ob. 1 for "political reasons" are displayed in orange, and the two outliers are in green. The figure indicates that, although the line of discontinuity identifies the two groups of treated and non-treated regions, the two-stage assignment mechanism behind the distribution of EUF (see Bodenstein and Kemmerling, 2011) makes some non-Ob. 1 regions receive a per capita amount of funds similar or slightly above than few Ob. 1

[5] Aragón is in the non-treated group, whereas Dytiki Makedonia is in the treated one. The criterion for outliers is to have received funds above the average plus 3 times the standard deviation of the respective treatment group in the restricted sample, excluding the lowest quarter for treated regions (in terms of initial level of per capita GDP) and the upper quarter for the non-treated regions. As we look at the maximum desirable intensity of payments, the removal of the treated region receiving the highest intensity of payments might seem counterintuitive. Nevertheless, given the high weight that OLS estimators assign to extreme values, even the presence of only one outlier has the potential of greatly influencing the results.

[6] The NUTS-2 level was adopted due to the very limited reliability of data at higher spatial disaggregation for the programming periods under analysis. For instance, even at the NUTS-3 level, the basic information on the geographic allocation of the EUF payments is the product of a mere estimation procedure in which the aggregated EUF data is artificially distributed among NUTS-3 regions.

regions. The normalisation moderately affects 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, particularly for the non-treated regions.

Insert Figure 1 about here

Figure 2 presents the geographical position of treated and non-treated regions in the EU-15: the standard core-periphery picture is clearly exhibited, with the treated regions mostly in the periphery. Because this study focuses on the intensity distribution among European regions, Figure 3 displays the geographical location of the regions with different deciles of treatment intensity (EUF by population) in the EU. In this figure, the core-periphery picture is less clear, indicating that several factors influenced the EUF regional intensity. In particular, the quality of the regional administration and the regional development strategies are crucial determinants of the outcome of the bargaining between national and regional authorities.

Insert Figures 2 and 3 about here

The distribution of the normalised EUF intensity is an important question, as the possibility of getting meaningful estimates depends on the variability of the normalised EUF 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 full and restricted samples. The intensity indicates a substantial variability between the two groups, and the shape of the distributions typically appears as a single mode and fat tails. As expected, the distribution is more concentrated when the sample size is reduced. No significant differences exist between the distributions of the normalised intensity[7] and an apparently modest area of overlap exists.

[7] This aspect is very important in our approach because we 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 with a smaller difference in the mean level, comparing such intensity is possible for most levels of treatment. Moreover, in this case once the treatment is controlled for, the differences in intensity can be thought as random, as it is assumed in our model.

Insert Figure 4 about here

Table 1 compares treated and non-treated regions with respect to different variables in the initial and final years of the research period. We also present the comparison in the large and restricted samples. Non-treated regions are generally smaller but more populated than the treated ones. As expected, they are richer and more productive. Still, the average per capita GDP growth is lower than that of the treated regions. As expected, the differences are smaller in the restricted sample than in the full sample.

Insert Table 1 about here

3. The impact of continuous treatment in an RDD framework

Our dataset on EUF transfers presents a discontinuity in the 1988-1990 per capita GDP, which allows using a quasi-experimental method deriving from an RDD approach (Thistlethwaite and Campbell, 1960; Hahn et al., 2001). This approach enables us to identify the causal effect of transfers on regional growth performances at the threshold in case of binary treatment. Our idea is to extend the RDD to the case of continuous treatment, considering intensity to be a cause of the impact heterogeneity. When the treatment is continuous, treatment effects are affected by 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, the effects may vary among units for each level of treatment. This is the covariate heterogeneity problem in the literature of programme evaluation with binary treatment, depending on the characteristics of each unit (see Becker et al., 2013; Percoco, 2017). Instead, this study focuses on another source of heterogeneity: 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. As in our study the number of observations is finite and limited, the heterogeneity in the covariates can dominate the heterogeneity in the level of treatment. Accordingly, we propose to combine designs and assume that, after conditioning on the observable variables affecting treatment assignment and the EUF intensity, treatment assignment (in differences from the mean for the treated and the non-treated sample) is as-if randomised for those regions near the Ob. 1 assignment threshold. Therefore, our approach is a combined design, where we consider heterogeneity in RDD after conditioning for pre-treatment covariates.[8]

The following simple representation describes the EUF framework: we assume two forms of treatment status (S) — a status with a high level of treatment $\left(S_h\right)$ and a status with a low level of treatment $\left(S_l\right)$. The treatment for each status varies in a continuous way around its mean, with the condition $E\left(S_h\right) > E\left(S_l\right)$. The level of treatment t is defined as the difference from the mean for each status: $t_h = S_h - E\left(S_h\right)$ and $t_l = S_l - E\left(S_l\right)$.

The common potential outcome approach in a continuous treatment framework can be applied to our context: $y_i\left(T\right)$ represents the set of potential outcomes, for each region *i*, given a random sample indexed by $i = 1 \ldots N$, and T represents the continuous variable indicating the treatment level t_i. The realised outcome y_i can be written as:

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

where D is the dummy variable indicating the treatment status ($D=1$ if the region is in the status with a high level of treatment, and $D=0$ if the region is in the status with a low level of treatment), and $y_i\left(t_i\right)$ 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) $\alpha\left(t\right) = E\left[Y\left(D=1\right) - Y\left(D=0\right) | T = t\right]$

[8] Although it is adopted in a different framework, a similar approach is presented in Keele et al. (2015).

The parameter $\alpha(t)$ 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 an 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 to the neighbourhood of the forcing variable threshold x_0, for every given t_i. We define the local average treatment level effect (LATLE):

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

where y_{1i} denotes the outcome with high treatment, y_{0i} the outcome with low treatment, $t_i = t_h = t_l$ the same deviation from the average intensity of the respective treatment status *S* and x_0 denotes the threshold value of 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:

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

In our case, the DRF relates each value of the EUF intensity to the compounded annual growth rate of per capita real GDP from 1994 to 2007. The estimation of the LATLE and the DRF in an RDD framework requires 3 different identifying assumptions. These assumptions adapt the HLATE framework proposed by Becker et al. (2013) to the case of continuous treatment:

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

This expression 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 treatment level* t_i *is continuous at the threshold* 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 $(t_i = t_h)$ and the untreated regions $(t_i = t_l)$, with $t_i = t_h = t_l$. The average jump is attributed to the difference in the average intensity of treatment between treated and not treated regions at the threshold.[9]

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 with the same level of treatment $t_i = t_h = t_l$ (in differences from the mean) are not different by some unobservable dimension. The condition is similar to the condition of weak unconfoundedness (CIA) in a GPS framework (Hirano and Imbens, 2004), but it is circumscribed around the threshold.[10]

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 that 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:

$$(5)\ LATLE\left(x_0,\ t_i\right) = E[y_{1i} \mid x_0,\ t_i,\ Z_i] - E[y_{0i} \mid x_0,\ t_i,\ Z_i]$$

[9] The plot of the treatment intensity distribution reported in Figure 6 in the next section indicates that assumption A2 is satisfied by the data.
[10] For the use of the CIA in an RDD framework, see Angrist and Rokkanen (2016).

where Z_i is a set of baseline covariates. We assume that Z_i captures the characteristics relevant to the probability of receiving 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:[11]

$$(6)\ DRF(t_i \mid x = x_0, Z_i) = E[y_i \mid x = x_0,\ t_i,\ Z_i]$$

Now we define the parametric control function for the LATLE identification. We start from the "classic" RDD framework:[12]

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

where Y is the compounded annual growth rate of per capita real GDP, x is the forcing variable (average per capita GDP in the 1988-1990 period) and D is the treatment dummy, when $b_0(.)$ and $b_1(.)$ are sufficiently smooth polynomial functions of x.

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

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

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

$$(9)\ Y = a + b_0(x) + g_0(t) + g_1 D + g_2(t) * D + b_1(x) * D$$

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[11] For the correct identification of the DRF, assumptions A1 and A3 are sufficient. It is also possible to representing 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.

[12] Although we adopt the fuzzy RDD in the paper, here we outline the case of sharp RDD to avoid cumbersome notation.

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 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, which exploits the RDD and conditions on the observables (Z) at the same time:

(10) $Y = a + b_0(x) + g_0(t) + g_1 D + g_2(t)*D + b_1(x)*D + h(Z)$

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. Defining the "average or normal effects of treatment given covariates" *(Y_n)*, which includes the discontinuity, as:

(11) $Y_n = a + b_0(x) + g_1 D + b_1(x)*D + h(Z)$

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) $Y - Y_n = g_0(t) + g_2(t)*D$

The second explanation is inside the Becker et al. (2013) framework. Intensity can be considered 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 (i.e., random assignment of the interaction variable conditional on x_i), where the interaction variable (i.e., the relative level of treatment in our study) is uncorrelated with the error term in the outcome equation, conditional on x_i (the forcing variable). Our framework assumes the relative level of treatment t_i is uncorrelated with the error term conditional on x_i and the covariates Z_i.

4. Results

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

Insert Figure 5 about here

In Figure 5, treated (i.e., Ob. 1) and non-treated regions are sharply separated. 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 EUF transfers intensity. These functions are estimated separately on both sides of the threshold.

The graphs indicate the typical shape of the RDD. On average, Ob. 1 regions demonstrate higher growth rates than other EU-15 regions, and this tendency is represented in the graph by a clear discontinuity. However, given our interest in the relationship between intensity and growth, the most interesting aspect of the figure is the concavity that it is created in the surface along the intensity axis. The relationship between intensity and growth is steady at first and then increases among the non-treated regions, but it increases to a maximum and then decreases for treated regions. This pattern is the same for the two normalisations. The figure then reveals how the effect of the intensity on treated regions has an internal maximum. This finding suggests that a maximum desirable amount of aid exists, which can be identified by the parametric model described above.

Disregarding the forcing variable, the relationship between the intensity of aid and growth can also be depicted on a two-dimensional plane. Figure 6 clearly indicates the different patterns of this relationship among treated and non-treated regions. For the non-treated regions displayed on the left side, the effect is first constant and then increasing; among the treated regions, the curvature underlined before is clear only in the restricted sample. The extreme values beyond the space bounded by the restricted sample appear as outliers compared to the basic relationship. This result is likely due to the peculiarities of these regions, which are either very under-populated or very deprived — characteristics that might influence their poor growth. The relationship between population and intensity also displays a negative sign, suggesting the presence of a reward for the smallest regions (see Figure B.1 in the Appendix).

Insert Figure 6 about here

We then move to the parametric estimation of the continuous fuzzy RDD, adapting the model presented in Section 3. Different order polynomials of the forcing variable can be introduced as regressors in the model 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 EUF transfers intensity at the threshold cannot be attributed to a missing non-linearity but exclusively to the Ob. 1 treatment. Accordingly, we use a third-order polynomial for the forcing variable where the parameters are allowed to differ to the right of the threshold from the left.[13] We additionally conditioned the equations to the following pre-treatment covariates: the overall population; the population density; the share of population over age 65; the employment rate for those 15-64 years old; labour productivity; and the

[13] Using the 2nd or the 4th order polynomials in the forcing variable leads to quantitatively similar estimates.

share of employment in the service sector and in the agricultural sector. Some of these variables control for idiosyncrasies among regions, while others are strongly linked to the determinants behind the assignment process of EUF. In fact, regional prosperity, national prosperity and the relative severity of the structural problems are the most relevant determinants of transfer intensity (Barbieri and Pellegrini, 1999). Their use strengthens the plausibility of our identifying assumptions, improves the efficiency of the RDD estimator in a small sample and mitigates concerns over the self-selection between small neighbourhoods across treated and not treated areas.

Table 2 presents 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 statistically significant at the 5% level, indicating the importance of EUF transfers intensity for GDP growth. We also relate the treatment dummy to the EUF intensity, allowing a different effect of intensity for treated and not treated regions. In this case we have a fully specified model (column 5), which is our preferred specification.

Insert Table 2 about here

In the case of the fully specified model, the effect captured by the treatment dummy is 1.1 percentage points more in terms of annual GDP growth for the population normalisation, when the intensity is average. This result is due to the strong difference in the average treatment between treated and not treated regions. This relationship is increasing with respect to the EUF transfers intensity but only up to a certain value. For example, the average annual per capita transfer in treated regions (restricted sample) is approximately €224. If we increase the transfers by 50%, the impact is substantially higher (1.8 ppts), while if we double the transfers the impact decreases to 0.9 ppts.

A simple way to graphically represent 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), the upper panel of Figure 7 indicates the average DRF of the compounded annual growth rate of per capita real GDP and the EUF 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 (EUF by population) and with the 90% confidence bands. The lower panel of Figure 7 presents the LATLE estimates both in absolute value (they directly derive from the estimates reported in Table 2) and in percent values (they report the LATLE graph we would obtain using the difference in percent value of the intensity between treated and non-treated regions instead of the difference in absolute values).[14] Figure 7 demonstrates that the dependent variable is an increasing function of the transfer intensity. The compounded annual growth rate of per capita real GDP is positive for each value of the intensity. For instance, a EUF intensity of €150 leads to a compounded annual growth rate of per capita real GDP of 2.7%, and a EUF intensity of €200 leads to an average GDP per capita growth rate of 3.2%. This result implies that the local average causal effect of increasing the EUF intensity from €150 to €200 is 3.2-2.7 = 0.5 percentage points, i.e., a 33% increase in EUF intensity causes a 19% increase in compounded annual growth rate of per capita real GDP for Ob. 1 NUTS-2 regions. However, the positive impact of the intensity on Ob. 1 NUTS-2 regions' growth is decreasing and it becomes statistically negligible after a certain threshold. Thus, evidence suggests that NUTS-2 regions receiving lower EUF intensity are much more sensitive to EUF intensity changes than NUTS-2 regions receiving higher EUF intensity levels and that additional transfers after a certain intensity threshold do not increase GDP.

Insert Figure 7 about here

[14] The LATLE estimates in absolute value are affected by a dimensionality issue due to the large difference in EUF intensity between Ob.1 and non-Ob. 1 regions. Indeed, an extra €50 for non-treated regions represent an increase in EUF transfers intensity of almost 1.5 times the average, while for the treated regions such increase is much more limited (0.2 times the average). Moreover, the dimensionality aspect affects also the common support that is necessarily reduced. To enlarge the common support and to check the validity of the LATLE estimates in absolute value, we compute the LATLE estimates also in percent values, as the use of differences in percent values substantially limits the aforementioned dimensionality issue. As the LATLE functions take on a similar functional form, we argue that this additional analysis backs up the hypothesis of the presence of a maximum desirable intensity.

Similar to Becker et al. (2012), we compute the maximum desirable EUF intensity for each model both with respect to the statistical significance of the treatment effect estimates and to their point estimates. For instance, using the fully specified model the maximum desirable EUF intensity is €305 for the point estimate (€275 for the statistical significance). The maximum desirable intensity estimates for each model are reported to Table 2. Note that based on Figure 7 we cannot ignore that the marginal effect of the treatment is constant and equal to zero after the maximum desirable EUF intensity.

Although our analysis is mainly focused on the effect of EUF on the per capita GDP growth rate, EU transfers might also affect other important variables such as income inequality, social cohesion, employment, and productivity. As we have access to some of these variables, in Table 3 we report the fully-specified model estimates for the compounded annual growth rate of real GVA, the employment growth rate and the labour productivity growth rate, all computed for the 1994-2007 period. The results concerning GVA and employment confirm the presence of a maximum desirable level of transfers and suggest that such maximum is higher than for GDP for these variables (€340 for the point estimate and €315 for the statistical significance). Concerning labour productivity, although the DRF takes on a functional form similar to the other dependent variables, no maximum desirable intensity exists, and the overall impact of EUF on labour productivity is slightly negative. This finding is not surprising, particularly where EUF pays for subsidies to firms. Bernini and Pellegrini (2011) argue that if the investment productivity curve is decreasing, the reduction in the investment cost generated by the subsidy drives the subsidised firm to invest in projects with lower than average productivity.

Insert Table 3 about here

Finally, using the combined results of EUF intensity on GDP, GVA and employment from the fully specified model, Figure 8 maps the NUTS-2 regions that received amounts of EUF transfers above the maximum desirable intensity among those close to the forcing variable threshold for each EUF intensity definition. Considering the point estimate (statistical significance) of the maximum desirable EUF intensity for the population normalisation, we find 6 (8) regions with an amount of transfers above the maximum desirable EUF intensity for our restricted sample of 156 regions.

Insert Figure 8 about here

5. Robustness

We assess the validity and the robustness of our results adopting various specification tests. First, in our context we cannot exclude that the intensity of the treatment is partially endogenous. For instance, regions using efficiently EUF and growing faster might receive more funds after a middle-period allocation revision. The automatic de-commitment and the performance reserve proceed in this direction. These mechanisms reduce inefficiencies in EUF spending and reward regions with good performance in the implementation of programmes. Our estimates can be biased in the presence of endogenous treatment intensity, and the effect of intensity overestimated. Therefore, we also use an instrumental variables (IV) approach for attenuating this potential issue.[15]

The IV identification strategy was based on the institutional context that determines the allocation of funds across Member States and regions. Following the suggestion of many authors (e.g. Bodenstein and Kemmerling, 2011, Charron, 2016), the identification of the aid intensity is based on a two-stage process: in the first stage, the amount of resources allocated to each country is identified by some clear and observable features such as eligible population, regional prosperity, national prosperity and severity of structural unemployment for Ob. 1 and 2, as declared in the Article 7 of Council Regulation 1260/1999 of 21 June 1999. These indicators, which are calculated as an average of three years before the programming period, are exogenous in our context. On the

[15] In order to do so, we replace Assumption 3 with Assumption 3b: the instruments satisfy the following conditions: i) they are weakly exogenous in the sense that they are uncorrelated with the error term; ii) they are correlated with the endogenous intensity variable after conditioning on the other covariates Z; and iii) they are uncorrelated with the dependent term except through the explanatory variable (again, conditioning on Z). The use of the instruments makes the treatment intensity as if randomly assigned.

other hand, given that in the second stage the bargaining between national and regional authorities occurs both before and after the start of the programming period, this raises an endogeneity issue. By using the variables that identify the "transparent procedures" of allocation before the programming period as instruments, we can break the "institutional" component of the intervention from the bargaining relationship that depends on a range of regional features (quality of administration, the regional development strategies and more), which are the fundamental sources of endogeneity in the equation.

As instruments, we use a dummy for the cohesion fund countries, the forcing variable relative to the country level, and the share of population relative to the country-wide population, with all covariates measured in 1994.[16] These variables should capture exogenous effects on EUF regional intensity as, after controlling for the covariates Z, the instruments should only affect the outcome variable via their effect on the treatment intensity. Indeed, the share of the relative population is a good approximation of the potential EUF share of the region; whereas the share of GDP is a correction factor. We present the results of the fully specified model when using the IV estimation in Table A.1 in the Appendix. Looking at the combined results of EUF intensity on GDP, GVA and employment, we find that the maximum desirable EUF intensity is slightly lower than the one reported in the main analysis (€310 for the point estimate and €270 for the statistical significance).

We then check whether our results change substantially using the beginning of period GDP normalisation (EUF/GDP 1994). The results for all model specifications and dependent variables are reported in Tables A.2 and A.3 in the Appendix. These estimates lead to qualitatively similar results, while the number of regions receiving transfers above the maximum desirable threshold decreases to 5 (6).

[16] The choice of the instruments is based on the indicators declared in the Article 7 of Council Regulation 1260/1999, after an identification and testing procedure: the dummy variable for the cohesion fund countries and the forcing variable relative to the country level are related to national and regional prosperity, and the share of population relative to the country-wide population is related to the share of eligible population, with all covariates measured in 1994. As the endogenous variable also appears in the squared and cubic form, we follow the approach proposed by Wooldridge (2010) and add the quadratic and cubic terms of the instruments as additional instruments before carrying out the IV regression.

We also need to check that the results do not depend on the use of the whole period 1994-2006 instead of splitting the period into 1994-1999 and 2000-2006. After selecting a restricted sample (as in the main analysis, we have dropped the lowest quarter for treated regions in terms of the initial level of per capita GDP and the upper quarter for the non-treated regions), we estimate the parametric RDD with 5 different model specifications. This test also allows us to check whether the few Ob. 1 status changes between the two programming periods had an impact on our results.[17] We find that the maximum desirable intensity is generally larger than the one reported in the main analysis, but this difference changes the final status of only a few regions. The results are reported in Table A.4 in the Appendix.

Spatial correlation can bias the estimation of our models. As data indicate 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.[18] 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 EUF intensity and consequently the presence of a maximum desirable intensity. The results are reported in Table A.5 in the Appendix. Besides, as Ob. 1 funds may be used to finance public infrastructure, generating not only local effects on the treated regions but also spillovers to neighbouring regions, we follow Becker et al. (2010) and test whether this leads to a downward-bias of the Ob. 1 treatment intensity effect estimates. This is why we exclude untreated regions sharing a border with at least one Ob. 1 region. Results are reported in Table A.6 and do not differ significantly from our main estimates.

Lastly, we also check the results do not depend on the exclusion of the 25% of regions whose level

[17] Some Ob. 1 regions for the 1994-1999 programming period were phased-out regions in the following programming period: "Highlands and the Islands" and "Northern Ireland" in the UK, "Southern and Eastern Region" in Ireland, "Flevoland" in the Netherlands, "Hainaut" in Belgium, "Corse" in France, "Molise" in Italy, "Lisboa" in Portugal and "Cantabria" in Spain. Some other regions were classified as Ob. 1 only in the 2000-2006 programming period: "South Yorkshire", "Cornwall and Isles of Scilly" and "West Wales and The Valley" in the UK and "Itä-Suomi" in Finland. As the per capita GDP of Ob. 1 regions becomes higher than 75% of the EU average, phasing-in or phasing-out transitional programs are put in place, reducing the amount of funds available to former Ob. 1 regions (Di Cataldo, 2017).

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

of per capita GDP in the period 1988-1990 was far away from the threshold. Nevertheless, the addition of these observations does not modify much the estimates. The results are reported in Table A.7 in the Appendix.

6. Conclusions

The intensity of EUF transfers is highly heterogeneous across regions, even within the same country. This study focuses on the estimation of the response of average annual GDP per-capita growth to changes in the intensity of regional EUF transfers. We use an original regional dataset, which overcomes some of the data issues in the past and which is fully coherent with Structural Funds Regulations for 1994–1999 and 2000–2006. 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 indicate a positive effect on average of EUF transfers on regional growth. The most interesting aspect is that the estimated conditional intensity-growth function is concave in our analysis interval and presents a maximum value, estimated in around €305-€340 per capita. After this value, the marginal efficiency of transfers is negative and statistically negligible. The larger the per capita transfers are, the smaller the regional growth rate. Therefore, these funds could have been allocated to other regions without reducing the effect for the single regions and plausibly increasing the effect on the other disadvantaged regions, particularly to those with sufficient human capital and good-enough institutions (see Becker et al., 2013).

Extending our results to all 208 regions, we find that 11 regions, accounting for 11% of the total EUF, received more than €340. In theory, if the contribution to these regions would have been reduced up to €340 per capita, the EU would have saved 5.1 billion Euros that could have been used to further help other least developed regions. Considering the results obtained from using the IV specification and the GDP normalisation, we find that the EU might have saved 7.4 and 8.0 billion Euros, respectively. Although these results are in line with the ones reported in Becker et al. (2012), we find that the concavity in the DRF is more prominent and a that smaller number of regions have exceeded the maximum desirable level of transfers. Therefore, our overall view on the EU regional policy is more positive than in Becker et al (2012), as the practical application of the policy is closer with its empirical maximum obtainable result.

The case of a minimum amount of funds is more complex. Signals hint that the effects are negligible for low levels of treatment, but a more comprehensive analysis is needed.

In summary, the empirical determination of the European regional policy is not so distant from the maximizing process implied by our model. However, our analysis demonstrates room for improving the allocation of EUF transfers among European regions, particularly reducing the transfers to regions where the transfer intensity is above the maximum desirable level. A reallocation of EU transfers from 11-15 regions (the 5-7% of total number of regions) to other less developed regions could be efficient and could strengthen regional convergence. Nevertheless, a great deal of caution should be exerted in a mechanical application of these results to the policy. This is based on the following two considerations. First, as we investigate the average impact of the EUF across Member States, our findings do not exclude the presence of idiosyncratic factors allowing for constant or increasing returns to investment for specific countries and regions. Second, the EUF transfers may have also other objectives apart from regional growth. Portions of the high EUF intensity of certain regions may be devoted to fulfil such diverse objectives, leading to a violation of the empirical relationship between EUF intensity and growth.

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References

Adorno V., Bernini C., and Pellegrini G. (2007). “The impact of capital subsidies: new estimations under continuous treatment”, *Giornale degli Economisti e annali di economia*, 120 (66): 67-92.

Angrist J.D., and Rokkanen M. (2016). “Wanna get away? Regression discontinuity estimation of exam school effects away from the cutoff”, *Journal of the American Statistical Association*, 110 (512): 1331-1344.

Anselin L. (2006). “Spatial econometrics”. In: T. Mills, K. Patterson, eds. Palgrave Handbook of econometrics, vol. 1. In: Econometric Theory. Basingstoke: Palgrave Macmillan, 901-969

Barbieri G., and Pellegrini G. (1999). “Coesione o sgretolamento? Un'analisi critica dei nuovi fondi strutturali”, *Rivista economica del Mezzogiorno,* a. XIII n. 1-2.

Becker S.O., Egger P.H., and von Ehrlich M. (2010). “Going NUTS: The effect of EU Structural Funds on regional performance”, *Journal of Public Economics,* 94: 578-590.

- (2012). “Too much of a good thing? On the growth effects of the EU's regional policy”, *European Economic Review,* 56 (4): 648-668.

- (2013). “Absorptive capacity and the growth and investment effects of regional transfers: a regression discontinuity design with heterogeneous treatment effects”, *American Economic Journal: Economic Policy,* 5 (4): 29-77

- (2016). “Effects of EU regional policy: 1989-2013”, CAGE Online Working Paper Series No. 271.

Bernini C., and Pellegrini G. (2011). “How are growth and productivity in private firms affected by public subsidy? Evidence from a regional policy”, *Regional Science and Urban Economics,* 41 (3): 253-265.

Bodenstein T., and Kemmerling A. (2011). “Ripples in a rising tide: Why some EU regions receive more structural funds than others”, *European Integration Online Papers,* 16 (1): 1-24

Bouayad-Agha S., Turpin N., and Védrine L. (2013). “Fostering the development of European regions: a spatial dynamic panel data analysis of the impact of Cohesion Policy”, *Regional Studies,* 47 (9): 1573-1593.

Charron, N. (2016). “Explaining the allocation of regional Structural Funds: The conditional effect of governance and self-rule”, *European Union Politics,* 17 (4): 638–659.

Dall'Erba S., and Fang F. (2015). “Meta-analysis of the impact of European Union Structural Funds on regional growth”, *Regional Studies*, doi: 10.1080/00343404.2015.1100285

Di Cataldo M. (2017). “The impact of EU Objective 1 funds on regional development: Evidence from the U.K. and the prospect of Brexit”, *Journal of Regional Science,* published online before print March 9, 2017.

Drukker D.M., Prucha I.R., and Raciborski R. (2013). “A command for estimating spatial-autoregressive models with spatial-autoregressive disturbances and additional endogenous variables”, *Stata Journal*, 13 (2): 287-301.

Esposti R., and Bussoletti S. (2008). “Impact of Objective 1 funds on regional growth convergence in the European Union: A panel-data approach”, *Regional Studies,* 42 (2): 159-173.

European Commission (2010). “Investing in Europe’s future”, Fifth report on economic, social and territorial cohesion, Luxembourg.

Giua M. (2017). “Spatial discontinuity for the impact assessment of the EU regional policy: the case of Italian Objective 1 regions”, *Journal of Regional Science,* 57 (1): 109-131.

Hahn J., Todd P., and van der Klaauw W. (2001), “Identification and estimation of treatment effects with a regression-discontinuity design”, *Econometrica,* 69 (1): 201-209.

Hirano K., and Imbens G.W. (2004). “The propensity score with continuous treatments”. In: Andrew G., Meng X.-L. (Eds.), Applied Bayesian modeling and causal inference from incomplete-data perspectives, Wiley, 73-84.

Imai K., and Van Dijk D.A. (2004). “Causal inference with general treatment regimes: generalizing the propensity score”, *Journal of the American Statistical Association,* 99: 854-866.

Keele L., Titiunik R., and Zubizarreta J. (2015). “Enhancing a geographic regression discontinuity design through matching to estimate the effect of ballot initiatives on voter turnout”, *Journal of the Royal Statistical Society: Series A,* 178 (1): 223-239.

Lee D.S., and Lemieux T. (2010). "Regression discontinuity designs in economics", *Journal of Economic Literature*, 48 (2): 281-355.

Mohl P., and Hagen T. (2010). "Do EU structural funds promote regional growth? New evidence from various panel data approaches", *Regional Science and Urban Economics*, 40 (5): 353-365.

Percoco M. (2017). "Impact of European Cohesion Policy on regional growth: Does local economic structure matter?", *Regional Studies*, 51 (6): 833-843.

Pellegrini G., Terribile F., Tarola O., Muccigrosso T., and Busillo F. (2013). "Measuring the effects of European regional policy on economic growth: A regression discontinuity approach", *Papers in Regional Science*, 92 (1): 217-233.

Rodríguez-Pose A., and Garcilazo E. (2015). "Quality of government and the returns of investment: examining the impact of cohesion expenditure in European regions", *Regional Studies*, 49 (8): 1274-1290.

Roemisch R. (2016). "Establishment of consolidated financial data 1989-2013", Directorate-General for Regional and Urban Policy, European Commission, Luxembourg.

Thistlethwaite D.L., and Campbell D.T. (1960). "Regression-discontinuity analysis: an alternative to the ex post facto experiment", *Journal of Educational Psychology*, 51 (6): 309-317.

Yang S., Imbens G.W., Cui Z., Faries D.E., and Kadziola Z. (2016). "Propensity score matching and subclassification in observational studies with multi-level treatments", *Biometrics*, published online before print March 17, 2016.

Wooldridge, J.M. (2010). "Econometrics Analysis of Cross Section and Panel Data", MIT Press, Cambridge, MA, 2nd edition.

Table 1: Descriptive statistics (mean) of NUTS-2 regions by treatment status

		Full sample (208 NUTS-2)		Restricted RDD sample (156 NUTS-2)	
		Treated (58 NUTS-2)	Non-treated (150 NUTS-2)	Treated (44 NUTS-2)	Non-treated (112 NUTS-2)
	GDP per capita compound growth rate (1994-2007)	2.30	2.03	2.38	2.08
	GDP per capita (EU-15 = 100, PPS) in 1988-1990	60.25	102.71	65.62	93.55
	EUF intensity (EUF/Population)	252.04	32.07	223.99	33.53
	Area (km^2)	18,444	14,994	18,808	16,502
1994	GDP (millions of euro, constant prices 2005)	21,942	46,906	24,228	36,467
	Population (millions of inhabitants)	1.523	1.889	1.663	1.657
	GDP per capita	14,486	23,938	14,858	21,826
	Population density (inhab./km^2)	236	438	275	311
	Employment rate, 15-64	53.14	65.58	53.47	63.56
	Productivity (GVA per hour worked, constant prices 2005)	20.29	29.89	20.73	28.61
	Share of population over 65	13.56	14.24	13.88	14.40
	Share in the service sector	63.35	68.60	63.47	68.01
	Share in the agricultural sector	13.46	4.20	13.18	4.58
2006	GDP (millions of euro, constant prices 2005)	31,571	62,173	34,996	48,970
	Population (millions of inhabitants)	1.623	1.989	1.760	1.746
	GDP per capita	19,099	30,470	20,039	27,879
	Population density (inhab./km^2)	243	463	290	323
	Employment rate, 15-64	59.86	68.14	60.14	68.28
	Productivity (GVA per hour worked, constant prices 2005)	24.34	37.15	24.71	35.61
	Share of population over 65	16.06	15.71	16.14	15.83
	Share in the service sector	68.16	73.93	68.57	73.35
	Share in the agricultural sector	8.99	2.88	8.26	3.16

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

Dependent variable: GDP per capita compound growth rate, 1994-2007					
	(1)	(2)	(3)	(4)	(5)
Dummy Treatment (D)	0.266	0.786	0.910	0.730	1.135
	(0.394)	(0.597)	(0.562)	(0.728)	(0.770)
Intensity	-	-	0.0046	0.0079	-0.0099
			(0.0023)**	(0.0025)***	(0.0053)*
Intensity Squared	-	-	-	-0.00003	0.0008
				(0.0002)	(0.0002)***
Intensity Cubic	-	-	-	-1.36e-07	-6.18e-06
				(9.15e-08)	(2.04e-06)***
Intensity*D	-	-	-	-	0.0187
					(0.0056)***
Intensity Squared*D	-	-	-	-	-0.0008
					(0.0002)***
Intensity Cubic*D	-	-	-	-	5.99e-06
					(2.04e-06)***
Polynomial order forcing variable	1	3	3	3	3
Other covariates	Yes	Yes	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	-	-	No	Yes	Yes
Maximum desirable intensity (stat. sign.)	N/A	N/A	N/A	€280	€275
Maximum desirable intensity (point est.)	N/A	N/A	N/A	€310	€305
R-squared	0.1196	0.1083	0.1635	0.2520	0.3196
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, population density, percentage of over 65, share in the service sector, share in the agricultural sector, productivity and employment rate among 15-64 years old, with all covariates measured in 1994.
***p<0.01, **p<0.05, *p<0.1.

Table 3: Continuous fuzzy RDD parametric estimates using alternative dependent variables: deviation from group means (Intensity = EUF / Population)

	Dep. Var.: GVA growth rate, 1994-2007	Dep. Var.: Employment growth rate, 1994-2007	Dep. Var.: Labour productivity growth rate, 1994-2007
Dummy Treatment (D)	2.087	3.132	-0.947
	(1.074)*	(0.858)***	(0.721)
Intensity	-0.0115	-0.0005	-0.0065
	(0.0049)**	(0.0046)	(0.0051)
Intensity Squared	0.0011	0.0011	-0.0004
	(0.0002)***	(0.0002)***	(0.0002)**
Intensity Cubic	-7.72e-06	-8.27e-06	3.09e-06
	(1.90e-06)***	(2.02e-06)***	(2.00e-06)
Intensity*D	0.0257	0.0159	0.0039
	(0.0058)***	(0.0051)***	(0.0056)
Intensity Squared*D	-0.0011	-0.0011	0.0004
	(0.0002)***	(0.0002)***	(0.0002)**
Intensity Cubic*D	7.42e-06	8.06e-06	-3.16e-06
	(1.90e-06)***	(2.02e-06)***	(2.00e-06)
Polynomial order forcing variable	3	3	3
Other covariates	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	Yes	Yes	Yes
Maximum desirable intensity (stat. sign.)	€295	€315	N/A
Maximum desirable intensity (point est.)	€320	€340	N/A
R-squared	0.4132	0.6191	0.4462
Nb. of treated regions	44	44	44
Nb. of non-treated regions	112	112	112

Note: See notes of Table 2.

Figure 1: EUF intensity by NUTS-2 regions

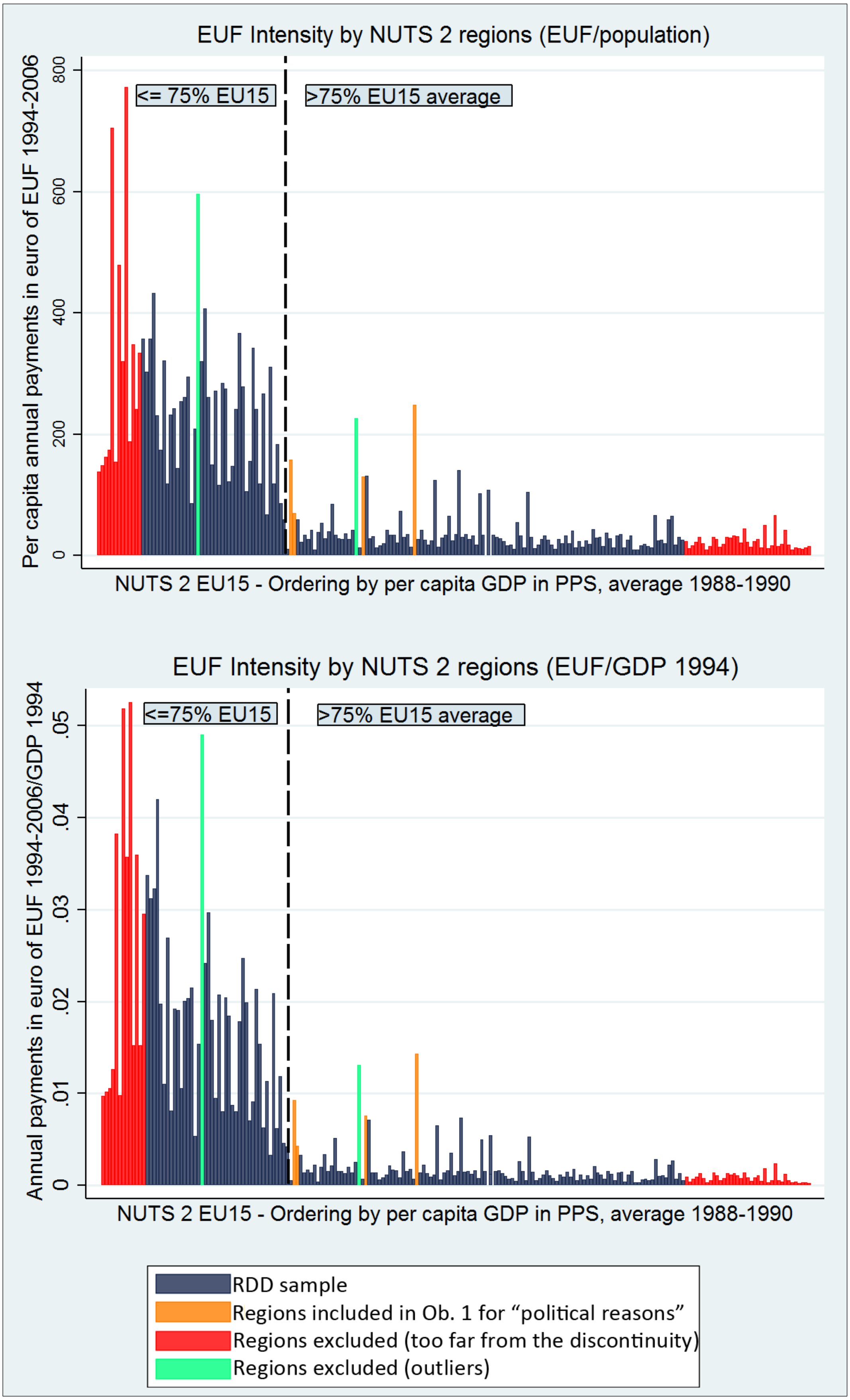


Figure 2: Eligible areas and treated and non-treated regions

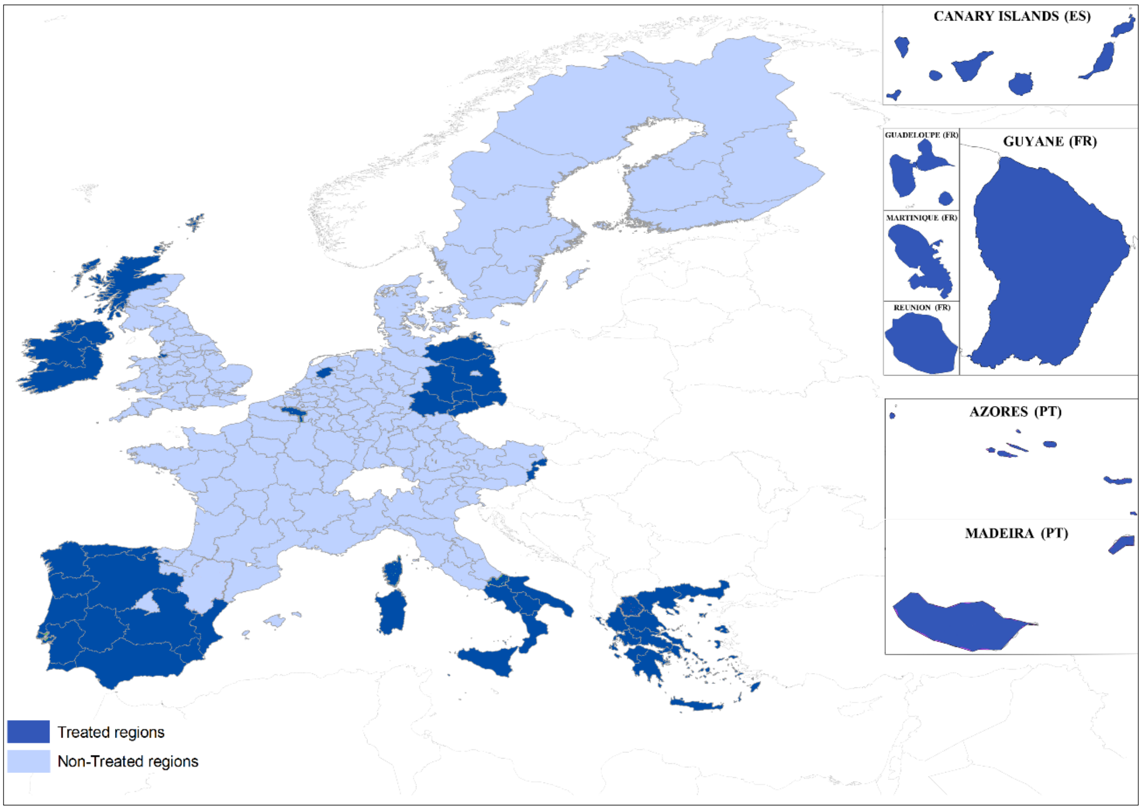


Figure 3: Regional distribution of the EUF (Intensity = EUF / Population)

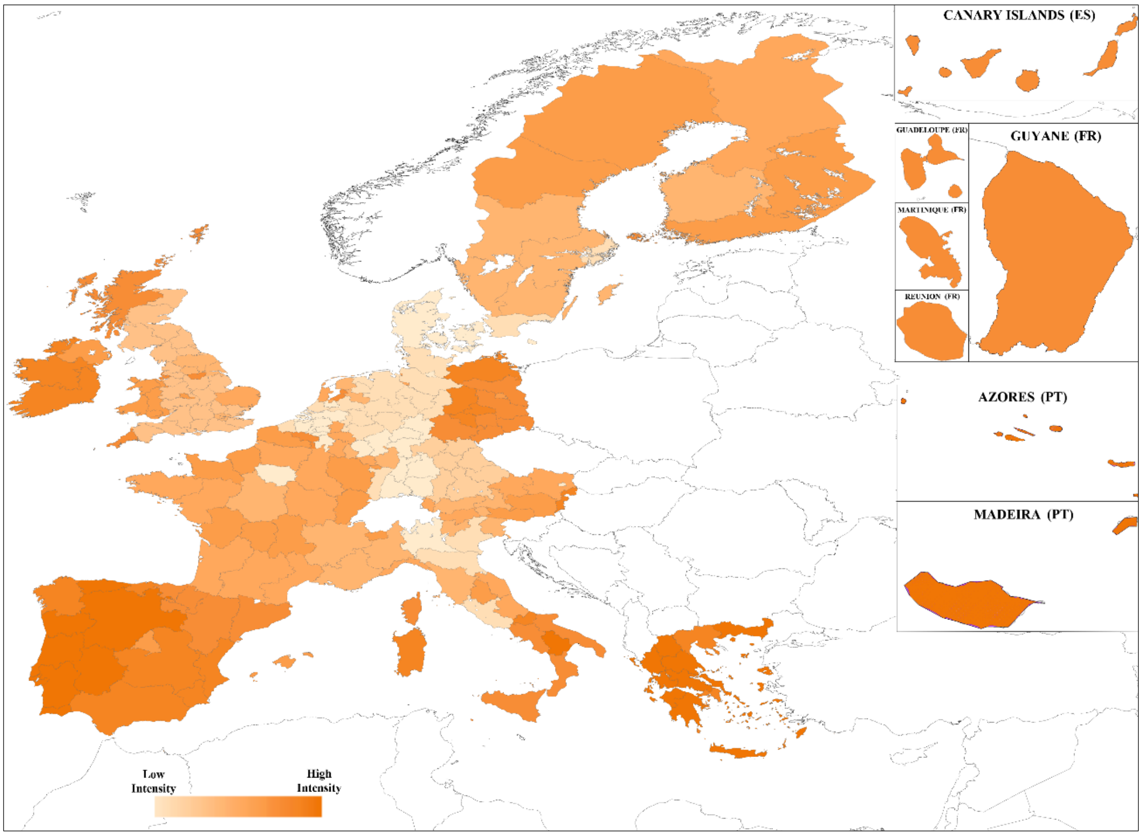


Figure 4: Kernel densities by treatment group

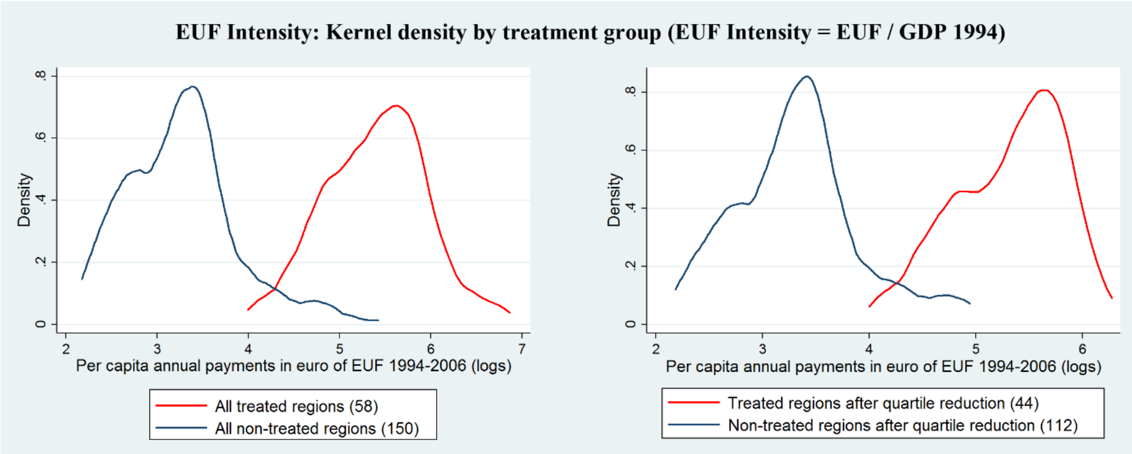
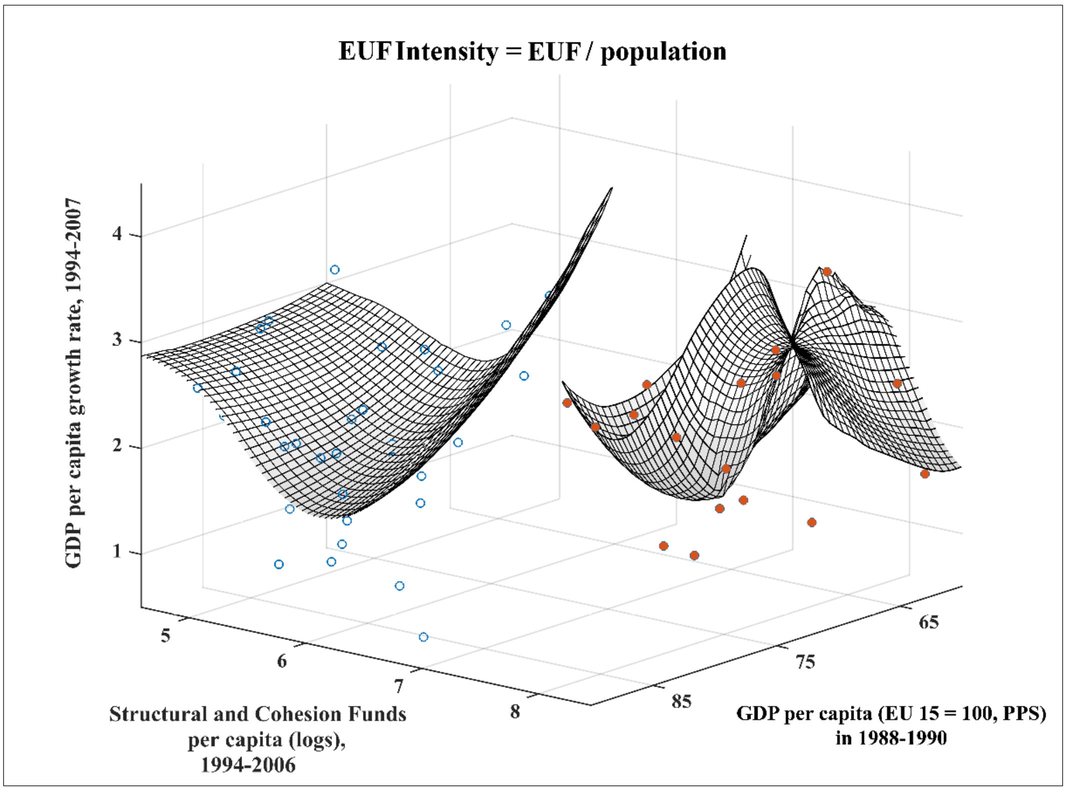
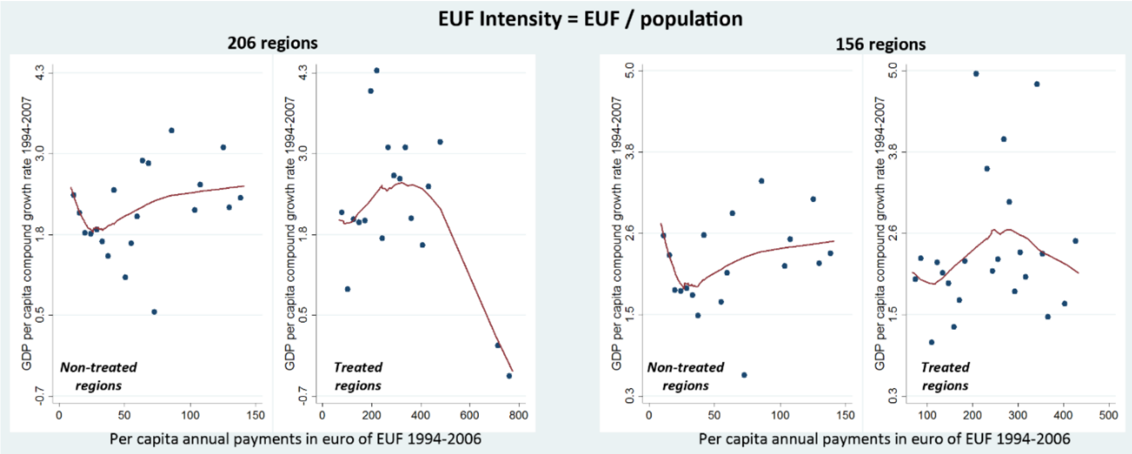


Figure 5: Relationship among the forcing variable, the GDP per capita growth rate and the EUF Intensity (restricted sample)



Notes: This figure illustrates the relationship between GDP per capita growth rate (1994-2007), 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. Regions included in Ob. 1 for "political reasons" have been omitted.

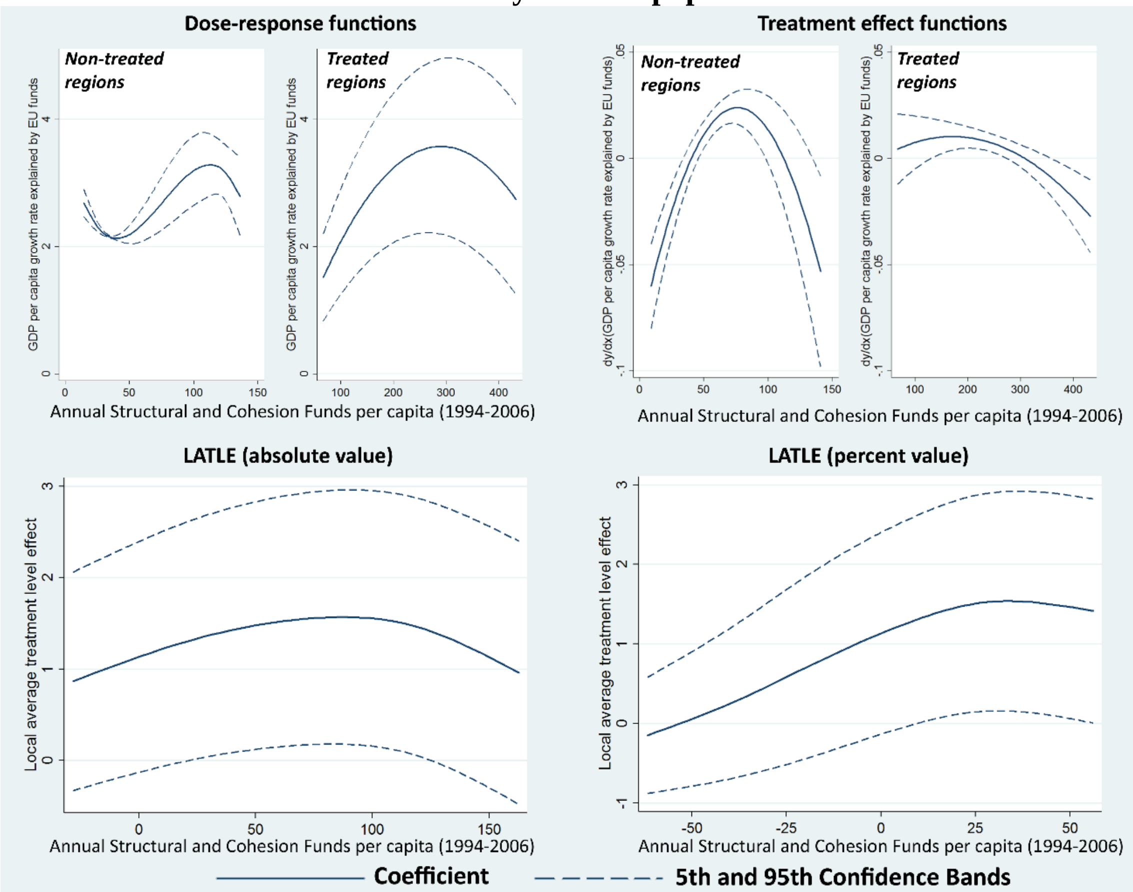
Figure 6: GDP per capita growth rate and the EUF Intensity (full and restricted sample)



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.

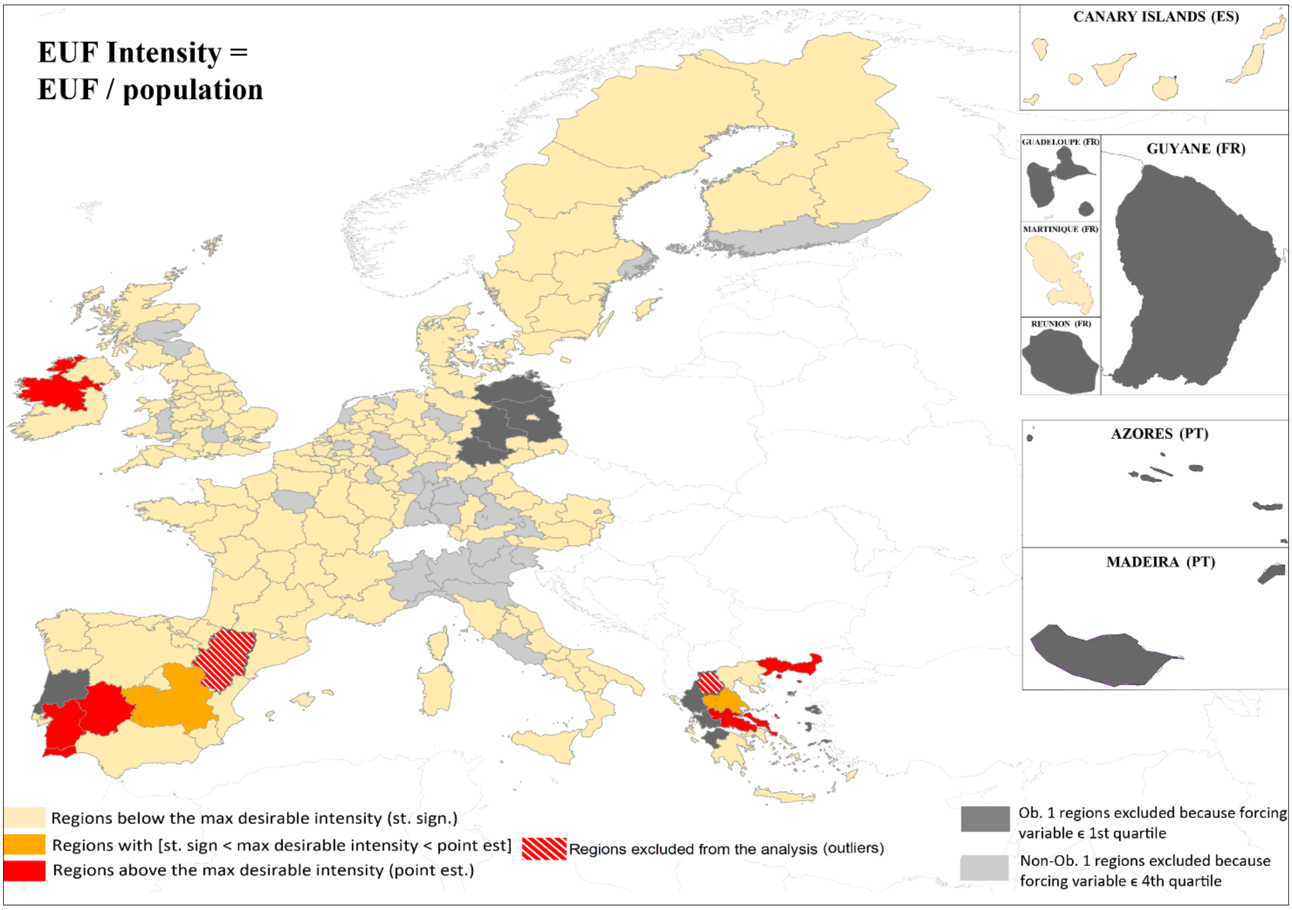
Figure 7: The effect of treatment intensity on regional growth (fully specified model)

EUF Intensity = EUF / population



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; (Lower panel): LATLE and 90% confidence bands limited to the common support between Ob. 1 and non-Ob. 1 regions.

Figure 8: Results by maximum desirable intensity (using the fully specified model results)



APPENDIX

Appendix A – Robustness checks tables

Table A.1: Continuous fuzzy RDD parametric estimates using the instrumental variables approach: deviation from group means (Intensity = EUF / Population)

	Dep. Var.: GDP per capita compound growth rate, 1994-2007	Dep. Var.: GVA growth rate, 1994-2007	Dep. Var.: Employment growth rate, 1994-2007	Dep. Var.: Labour productivity growth rate, 1994-2007
Dummy Treatment (D)	2.262	2.266	2.057	0.487
	(1.157)*	(1.155)**	(0.762)***	(1.006)
Intensity	-0.0196	0.0034	0.0180	-0.0042
	(0.0182)	(0.0230)	(0.0141)	(0.0206)
Intensity Squared	0.0015	0.0014	0.0008	-0.0001
	(0.0008)*	(0.0008)*	(0.0005)	(0.0007)
Intensity Cubic	-0.00001	-0.00001	-6.50e-06	-6.70e-07
	(7.87e-06)	(7.56e-06)*	(5.44e-06)	(6.60e-06)
Intensity*D	0.0247	0.0080	-0.0003	-0.0062
	(0.0175)	(0.0206)	(0.0138)	(0.0187)
Intensity Squared*D	-0.0016	-0.0015	-0.0008	0.0001
	(0.0008)*	(0.0009)*	(0.0006)	(0.0008)
Intensity Cubic*D	0.00001	0.00001	6.06e-06	1.12e-06
	(8.09e-06)	(7.83e-06)*	(5.68e-06)	(6.77e-06)
Polynomial order forcing variable	3	3	3	3
Other covariates	Yes	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	Yes	Yes	Yes	Yes
Maximum desirable intensity (stat. sign.)	€190	€210	€270	N/A
Maximum desirable intensity (point est.)	€250	€285	€310	N/A
Nb. of treated regions	44	44	44	44
Nb. of non-treated regions	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). As instruments, we use a dummy for the cohesion fund countries, the forcing variable relative to the country level, and the share of population relative to the country-wide population, with all covariates measured in 1994.
***p<0.01, **p<0.05, *p<0.1.

Table A.2: Continuous fuzzy RDD parametric estimates: deviation from group means (Intensity = EUF / GDP 1994)

Dependent variable: GDP per capita compound growth rate, 1994-2007					
	(1)	(2)	(3)	(4)	(5)
Dummy Treatment (D)	0.266	0.786	1.066	1.235	1.667
	(0.394)	(0.597)	(0.644)*	(0.945)	(0.992)*
Intensity	-	-	52.295	64.569	-137.226
			(27.116)*	(33.152)*	(118.973)
Intensity Squared	-	-	-	-6,733	257,557
				(3,481)*	(70,917)***
Intensity Cubic	-	-	-	121,990	-3.78e+07
				(130,475)	(1.31e+07)**
Intensity*D	-	-	-	-	178.663
					(118.883)
Intensity Squared*D	-	-	-	-	-265,896
					(70,722)***
Intensity Cubic*D	-	-	-	-	3.81e+07
					(1.31e+07)**
Polynomial order forcing variable	1	3	3	3	3
Other covariates	Yes	Yes	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	-	-	No	Yes	Yes
Maximum desirable intensity (stat. sign.)	N/A	N/A	N/A	0.0150	0.0135
Maximum desirable intensity (point est.)	N/A	N/A	N/A	0.0215	0.0190
R-squared	0.1196	0.1083	0.1367	0.2328	0.2771
Nb. of treated regions	44	44	44	44	44
Nb. of non-treated regions	112	112	112	112	112

Note: See notes of Table 2.

Table A.3: Continuous fuzzy RDD parametric estimates using alternative dependent variables: deviation from group means (Intensity = EUF / GDP 1994)

	Dep. Var.: GVA growth rate, 1994-2007	Dep. Var.: Employment growth rate, 1994-2007	Dep. Var.: Labour productivity growth rate, 1994-2007
Dummy Treatment (D)	2.945	4.312	-1.375
	(1.302)**	(1.044)***	(0.784)*
Intensity	-147.367	70.397	-149.522
	(117.422)	(95.170)	(108.938)
Intensity Squared	353,484	367,846	-90,500
	(62,095)***	(76,120)***	(78,259)
Intensity Cubic	-4.93e-07	-5.26e-07	1.31e-07
	(1.22e-07)***	(1.41e-07)***	(1.44e-07)
Intensity*D	269.722	108.222	72.611
	(112.676)**	(93.769)	(105.508)
Intensity Squared*D	-360,102	-374,755	89,976
	(62,324)***	(76,661)***	(78,097)
Intensity Cubic*D	4.93e-07	5.26e-07	-1.30e-07
	(1.22e-07)***	(1.41e-07)***	(1.44e-07)
Polynomial order forcing variable	3	3	3
Other covariates	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	Yes	Yes	Yes
Maximum desirable intensity (stat. sign.)	0.0200	0.0255	N/A
Maximum desirable intensity (point est.)	0.0255	0.0290	N/A
R-squared	0.3478	0.5583	0.4379
Nb. of treated regions	44	44	44
Nb. of non-treated regions	112	112	112

Note: See notes of Table 2.

Table A.4: Continuous fuzzy RDD parametric estimates: deviation from group means (Intensity = EUF / Population) – 2 different Programming Periods

Dependent variable: GDP per capita compound growth rate 1994-2000 (for PP 1994-1999) and 2000-2007 (for PP 2000-2006)					
	(1)	(2)	(3)	(4)	(5)
Dummy Treatment (D)	0.180	0.648	0.875	1.127	1.331
	(0.398)	(0.517)	(0.583)	(0.915)	(0.948)
Intensity	-	-	0.0036	0.0057	-0.0088
			(0.0024)	(0.0025)**	(0.0053)
Intensity Squared	-	-	-	-1.39e-06	0.0004
				(0.00002)	(0.0001)***
Intensity Cubic	-	-	-	-7.56e-08	-1.88e-06
				(8.13e-08)	(1.04e-06)*
Intensity*D	-	-	-	-	0.0153
					(0.0059)***
Intensity Squared*D	-	-	-	-	-0.0004
					(0.0001)***
Intensity Cubic*D	-	-	-	-	1.79e-06
					(1.05e-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	0	1
Maximum desirable intensity (stat. sign.)	N/A	N/A	N/A	€295	€275
Maximum desirable intensity (point est.)	N/A	N/A	N/A	€375	€365
R-squared	0.2177	0.2274	0.2485	0.2628	0.2870
Nb. of treated regions	83	83	83	83	83
Nb. of non-treated regions	225	225	225	225	225

Note: Clustered standard errors at the NUTS-2 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 pre-treatment covariates include population, population density, percentage of over 65, share in the service sector, share in the agricultural sector, productivity and employment rate among 15-64 years old.
***p<0.01, **p<0.05, *p<0.1.

Table A.5: Continuous fuzzy RDD parametric estimates using the Spatial Error Model: deviation from group means (Intensity = EUF / Population)

Dependent variable: GDP per capita compound growth rate, 1994-2007				
	(1)	(2)	(3)	(4)
Dummy Treatment (D)	-0.383	0.062	0.402	0.620
	(0.647)	(0.733)	(0.591)	(0.600)
Intensity	0.0026	-0.0132	0.0079	-0.0073
	(0.0031)	(0.0050)***	(0.0025)***	(0.0049)
Intensity Squared	-0.00001	0.0006	-0.00003	0.0007
	(0.00001)	(0.0002)***	(0.00002)*	(0.0002)***
Intensity Cubic	-1.06e-08	-3.90e-06	-1.54e-07	-5.81e-06
	(7.78e-08)	(1.82e-06)**	(8.93e-08)*	(1.97e-06)***
Intensity*D	-	0.0187	-	0.0159
		(0.0048)***		(0.0051)***
Intensity Squared*D	-	-0.0006	-	-0.0007
		(0.0002)***		(0.0002)***
Intensity Cubic*D	-	3.78e-06	-	5.61e-06
		(1.81e-06)**		(1.98e-06)***
ρ (rho)	4.221	3.159	0.255	0.226
	(1.464)***	(1.037)***	(0.097)***	(0.102)**
Spatial Matrix	Euclidean	Euclidean	Rook	Rook
Polynomial order forcing variable	3	3	3	3
Other covariates	Yes	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	No	Yes	Yes	Yes
Maximum desirable intensity (statistical significance)	N/A	€245	€275	€270
Maximum desirable intensity (point estimate)	€300	€310	€305	€305
Nb. of treated regions	44	44	44	44
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 spivreg.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, population density, percentage of over 65, share in the service sector, share in the agricultural sector, productivity and employment rate among 15-64 years old, with all covariates measured in 1994.
***p<0.01, **p<0.05, *p<0.1.

Table A.6: Continuous fuzzy RDD parametric estimates with spatial exclusion: deviation from group means (Intensity = EUF / Population)

Dependent variable: GDP per capita compound growth rate, 1994-2007					
	(1)	(2)	(3)	(4)	(5)
Dummy Treatment (D)	0.375	0.636	0.713	0.637	1.302
	(0.453)	(0.610)	(0.539)	(0.640)	(0.697)*
Intensity	-	-	0.0050	0.0078	-0.0082
			(0.0025)**	(0.0028)***	(0.0061)
Intensity Squared	-	-	-	-0.00003	0.0015
				(0.0002)*	(0.0004)***
Intensity Cubic	-	-	-	-1.19e-07	-0.00002
				(9.88e-08)	(6.51e-06)***
Intensity*D	-	-	-	-	0.0171
					(0.0065)***
Intensity Squared*D	-	-	-	-	-0.0016
					(0.0004)***
Intensity Cubic*D	-	-	-	-	0.00002
					(6.51e-06)***
Polynomial order forcing variable	1	3	3	3	3
Other covariates	Yes	Yes	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	-	-	No	Yes	Yes
Maximum desirable intensity (stat. sign.)	N/A	N/A	N/A	€265	€270
Maximum desirable intensity (point est.)	N/A	N/A	N/A	€300	€305
R-squared	0.1462	0.1377	0.2081	0.3042	0.3686
Nb. of treated regions	44	44	44	44	44
Nb. of non-treated regions	90	90	90	90	90

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 restricted sample with the additional exclusion of all non-Ob. 1 regions sharing a border with at least one Ob. 1 region. Other covariates include population, population density, percentage of over 65, share in the service sector, share in the agricultural sector, productivity and employment rate among 15-64 years old, with all covariates measured in 1994.
***p<0.01, **p<0.05, *p<0.1.

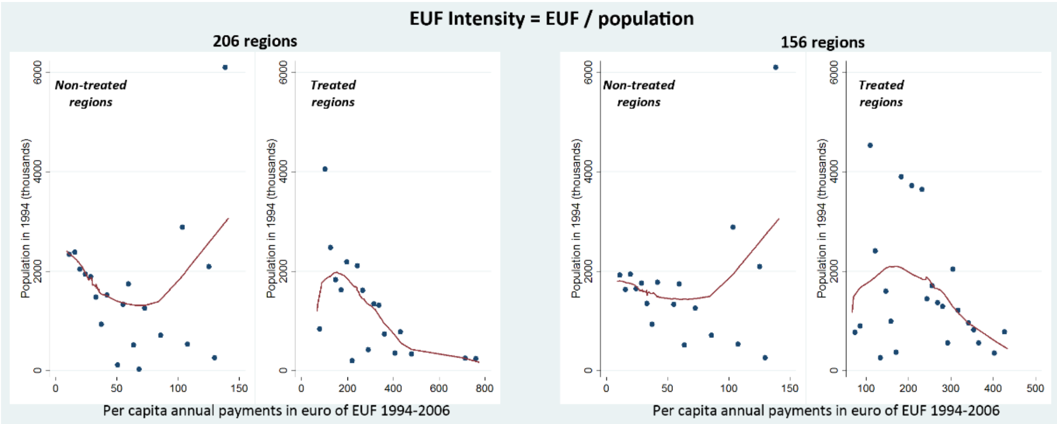
Table A.7: Continuous fuzzy RDD parametric estimates: deviation from group means (Intensity = EUF / Population) – using the full sample

Dependent variable: GDP per capita compound growth rate, 1994-2007					
	(1)	(2)	(3)	(4)	(5)
Dummy Treatment (D)	0.567 (0.290)*	0.429 (0.394)	0.606 (0.428)	1.141 (0.667)*	1.364 (0.684)**
Intensity	-	-	0.0034 (0.0016)**	0.0040 (0.0022)*	-0.0147 (0.0058)**
Intensity Squared	-	-	-	-0.00002 (0.00002)	0.0009 (0.0003)***
Intensity Cubic	-	-	-	4.70e-08 (4.66e-08)	-7.22e-06 (3.70e-06)
Intensity*D	-	-	-	-	0.0179 (0.0056)***
Intensity Squared*D	-	-	-	-	-0.0010 (0.0003)***
Intensity Cubic*D	-	-	-	-	7.28e-06 (3.70e-06)**
Polynomial order forcing variable	1	3	3	3	3
Other covariates	Yes	Yes	Yes	Yes	Yes
Intensity parameters jointly stat. sign. (5% level)	-	-	No	No	Yes
Maximum desirable intensity (stat. sign.)	N/A	N/A	N/A	€215	€205
Maximum desirable intensity (point est.)	N/A	N/A	N/A	€390	€300
R-squared	0.1229	0.1736	0.2023	0.2129	0.2700
Nb. of treated regions	56	56	56	56	56
Nb. of non-treated regions	147	147	147	147	147

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 whole sample except for the outliers (the criterion for outliers is to have received funds above the average plus 3 times the standard deviation of the respective treatment group). Other covariates include population, population density, percentage of over 65, share in the service sector, share in the agricultural sector, productivity and employment rate among 15-64 years old, with all covariates measured in 1994.
***p<0.01, **p<0.05, *p<0.1.

Appendix B – Relationship between population and the EUF Intensity

Figure B.1: Population and the EUF 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.