

Measuring the Impact of the European Regional Policy on Economic Growth: a Regression Discontinuity Design Approach

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Abstract

Given the increasing share of the EU budget devoted to Regional Policy, several studies have tried to identify the impact of Structural Funds on economic growth and convergence. However, so far no consensus has been reached on the policy effectiveness, due to both limitations in data availability and comparability at regional level, and the difficulties in isolating the effects of the policy from the confounding effect of other factors. The purpose of this paper is to assess the effects of UE Regional Policy, using a non-experimental comparison group design - the regression discontinuity design (henceforth RDD). To this end, we properly build up an economic and financial regional data set, fully coherent and comparable. We exploit the allocation rule of regional UE transfer: only regions with a per capita GDP level below 75% of the EU average qualify for Objective 1 funds. The sharp RDD is based to the jump in the probability of EU transfer receipt at the 75% cut-off point. Our findings show a positive, but moderate, policy effect on regional growth. The per capita GDP of the “treated” regions (regions in Obj. 1) grows on yearly average in the period 1995-2006 0.8 percentage points more than that in the non treated regions.

JEL: O18, O47, C14.

Keywords: cohesion policy, regional growth, program evaluation, regression discontinuity design.

1. Introduction

The aim of this paper is to assess the effectiveness of EU Regional policy, using a reliable and comparable dataset and a non-experimental comparison group design - the regression discontinuity design (henceforth RDD) - to evaluate the causal effects of the policy on regional economic growth. Regional policy - or Cohesion policy - is one of the key axes of EU integration, together with single market and monetary union. In the period 2007-2013, a relevant share of the EU budget – around 36 per cent (€347 billion) – is intended for this purpose.

Given the increasing share of the EU budget devoted to Regional policy since the mid-1970's, numerous studies have tried to shed light on the policy's contribution to economic growth and convergence. However, after more than thirty years of policy intervention, empirical evidence remains mixed and contradictory. No consensus exists on the effectiveness of Cohesion policy.

While some econometric analyses suggest that Regional policy has a significant positive impact on growth and convergence (de la Fuente and Vives, 1995; Cappelen *et al.*, 2003; Beugelsdijk and Eijffinger, 2005), others find only conditionally-positive effects, depending on the quality of institutions, country's openness, (see, *inter alia*, Ederveen *et al.*, 2002 and 2006). Finally, a large amount of works estimates the impact as not statistically significant or even negative (Fagerberg and Verspagen 1996; Boldrin and Canova, 2001; Dall'erba and Le Gallo, 2008; Hagen and Mohl, 2008). This mixed evidence is due not only to limitations in data availability and comparability at regional level, but also (and mainly) to the difficulties faced when isolating the effects of Regional policy from the confounding ones induced by other factors. Close in spirit to the above mentioned literature, and in order to overcome the above referred difficulties, we depart from it as we identify the Regional policy effects on the basis of the so called Regression discontinuity design. This method, rarely used in the evaluation of Cohesion policy programmes, compares the economic scenario arising under policy interventions with a “counterfactual” situation - what would have

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happened if the policies were not implemented¹. Non-experimental comparison group designs have been used to our knowledge only in two recent papers. Mohl and Hagen (2008) apply a generalized propensity score to indicate that Structural funds payments have a positive, but not statistically significant, impact on the regions growth rates. Becker *et al.* (2008), in a paper close to the approach we use, inferred causal effects of Objective 1 interventions on EU regions using a regression discontinuity design based on panel data at NUTS 3 level. They isolate and identify the Regional policy role in fostering economic cohesion. However, the paper does not fully exploit the consequences of the RDD in terms of estimation and testing.

Although *a priori* the RDD allows to isolate regional policy impact, the analysis of EU regional policy is still complex, for several reasons. Not only the limited number of observations, but also the high variability of regional growth with respect to the initial level of GDP per capita can strongly affect the statistical precision of estimates. In order to overcome these potential pitfalls, in the paper we perform different analyses, using parametric and non parametric estimators, and modifying a number of key characteristics (e.g. specification, sample, bandwidth, kernel function). Moreover, different tests are presented as suggested by Lee and Lemieux (2009) and Imbens and Lemieux (2008). Quite interestingly, we find that EU Regional Policy in Objective 1 regions has a positive and significant impact on growth. The comparison between regions' performance points to an annual GDP per capita growth difference of 0.6-0.9 percentage points in favour of Objective 1 regions, over the period 1995-2006.

2. The EU Cohesion Policy

Cohesion Policy is a policy concerning the development of regions and is implemented at a regional level. Its intensity, at a territorial level, varies both in terms of goals and funds addressed to different areas. The bulk of the Cohesion Policy concerns the so called Objective 1 of the previous programming periods (now Convergence Objective). It aims at speeding-up the convergence of the least-developed regions, which are defined as regions (in statistical terms, NUTS I or NUTS II level, according to the member states) with per capita GDP in purchase parity is less than 75 per cent of the EU average. At present, this Objective concerns 84 regions as well as a population of 170 million plus another 16 regions with 16.4 million inhabitants and a GDP only slightly above the threshold of 75 per cent due to the statistical effect of recent enlargement processes. The latter receives assistance on a transitional basis within the same territorial Objective ("phasing out" regions in the 2007-2013 regulation).

3. Evaluating the effect of EU regional policy using a regression discontinuity design

The key issue when evaluating public policies is to identify their own effect apart from the ones determined by other factors. The Regression Discontinuity Design (RDD), an evaluation method, introduced by Thistlethwaite and Campbell (1960), well fits this aim. Traditionally, it develops as a pre-test - post-test program-comparison group strategy where participants are assigned to the program or comparison groups on the basis of a cut-off point properly defined. The rationale at the basis of the RDD is that the average outcome for units marginally above (res. below) the cut-off point can represent a counterfactual for the "treated" group just below (res. above) the threshold.

Admittedly, the observed variable (namely, the so called forcing variable) may itself be associated with the outcome of the treatment, but this association is assumed to be smooth. Therefore any discontinuity of the conditional expectation of the outcome as a function of the forcing variable at the cut-off point is interpreted as evidence of a causal effect of the treatment. Differently from randomised experiments, where the randomised sample ensures the comparison between statistical units (in our case, NUTS 2 regions) belonging to the treated or non-treated group, in the RDD the observations systematically differ among the two groups. This implies a specific selection rule to distinguish the observations belonging to the treated or non-treated group.

¹ Remarkable exceptions that have recently tried to apply counterfactual methods in the evaluation of the impact of UE regional policy are Mohl and Hagen (2008) and Becker *et al.* (2008).

In particular, the design requires the identification of a cut-off point to create a discontinuity in the treatment assignment mechanism (in our case, eligible or not eligible for funding from EU Structural Funds)².

Although, it only identifies treatment effects locally at the cut-off-point, its results can be applied to each unit which has a positive probability to be located near the cut-off point (Lee, 2008). Also, from a methodological point of view, inferences which are drawn from a well-implemented RDD are comparable, in terms of internal validity, to the findings emerged from randomized experiments, such as matching on observables, difference-in-differences, and instrumental variables. Finally, it bypasses many of the questions related to model specification, both the problem of variables identification and the one related to their functional form (Hahn et al., 2001).

In this paper, we use the RDD approach for estimating the effects of regional policy on the economic growth in EU³. The regions whose per capita GDP is less than 75 per cent of the EU average (i.e. eligible for funding from the Structural funds under Objective 1) are considered as being comparable with those just above the cut-off point (the 75 per cent threshold) not eligible for funding; the forcing variable is the level of regional GDP per capita and the treatment is the EU Structural funds⁴.

Let us briefly describe the approach⁵. Let $Y_i(1)$ and $Y_i(0)$ denote the potential outcome of region i , where $Y_i(1)$ is the GDP growth of Objective 1 region (receiving Structural Funds) and $Y_i(0)$ is the economic growth of non Objective 1 region. We are interested in the difference $Y_i(1) - Y_i(0)$. Due to the problem of causal inference (Holland, 1986), we cannot observe this difference at the unit level. For each unit i we observe only one of the two outcome, either $Y_i(0)$ or $Y_i(1)$. Accordingly, we focus on average effects of the treatment.

Let W_i denote the treatment variable, with $W_i=1$ if the region receives EU Structural Funds (i.e. is qualified as Objective 1) and $W_i=0$ if the region does not receive the treatment (i.e. and therefore is non Objective 1). The outcome (GDP growth) for region i can be written as:

$$Y_i = (1 - W_i)Y_i(0) + W_iY_i(1) = \begin{cases} Y_i(0) & \text{if } W_i = 0 \\ Y_i(1) & \text{if } W_i = 1 \end{cases} \quad (1)$$

We consider a vector of pre-treatment variables Z_i , which are not affected by the treatment. Within these variables, we isolate the covariate X_i : receiving the treatment (i.e. receiving Structural Funds) is assumed to only depend on whether the level of X_i is below or above the fixed threshold. In our case, X_i is the level of GDP per head (expressed in terms of purchasing power standards, PPS) as a percentage of the EU average (EU-15=100) in the period 1988-1990. Accordingly, for a treated region (i.e. a region eligible for funding from the Structural Funds under Objective 1) the value X_i is less than the cut-off point of 75 per cent:

$$W_i = 1\{X_i \leq c\} \quad \text{where } c=75.$$

Regions with X_i above the value c (non Objective 1) are assigned to the control group (regions not eligible for funding). For finding evidence of an average causal effect of the treatment, we need to verify a discontinuity in the conditional expectation of the outcome (regional GDP growth)

$$\lim_{x \downarrow c} E[Y_i | X_i = x] - \lim_{x \uparrow c} E[Y_i | X_i = x]. \quad (2)$$

In the case of sharp RDD, the average causal effect of the treatment at the discontinuity point is:

$$\tau_{SRD} = E[Y_i(1) - Y_i(0) | X_i = c]. \quad (3)$$

In order to justify this averaging we make a smoothness assumption (i.e. that the relation

² Under certain conditions, the selection of units near the cut-off point can be considered as a randomised experiment. Lee (2008) showed that if units are unable to *precisely* control the forcing variable near the known cut-off point, variation in the treatment status in a neighbourhood of the threshold is randomized, as in randomised experiments. Even when units have some influence over the forcing variable, as long as this control is imprecise – that is, the ex ante density function of the forcing variable is continuous – the consequence will be local randomization of the treatment.

³ See Lee and Lemieux (2009) for a survey of the areas of applied economic research that have used the RDD.

⁴ We refer the interested reader to Imbens and Lemieux (2007) for details.

⁵ The basic framework is closely related to Imbens and Lemieux (2007), to which the reader is referred for further details.

between X_i and Y_i is smooth around c), known in the literature as “continuity of conditional regression functions”.

$E[Y(0)|X = x]$ and $E[Y(1)|X = x]$ are continuous in X .

This assumption is stronger than required, as we will only use continuity at $X=c$, but it is not reasonable to assume continuity for one value of the covariate X . Under this assumption:

$$E[Y(0)|X = c] = \lim_{x \downarrow c} E[Y(0)|X = x] = \lim_{x \downarrow c} E[Y(0)|W = 0, X = x] = \lim_{x \downarrow c} E[Y|X = x] \quad (5)$$

Thus, the value of the counterfactual outcome in $X=c$ is equal to the limit of the conditional expected value of the outcome for non treated regions. Similarly, for treated regions:

$$E[Y(1)|X = c] = \lim_{x \uparrow c} E[Y|X = x] \quad (6)$$

Accordingly, the average effect writes as:

$$\tau_{SRD} = \lim_{x \uparrow c} E[Y|X = x] - \lim_{x \downarrow c} E[Y|X = x]. \quad (7)$$

Given this, we need to estimate two limits, approaching c from right and left⁶. Given the sensitivity of results to the estimator and bandwidth in the non parametric case, and to model specification in the parametric case, we will present different analyses and estimations to evaluate the robustness of our conclusions. Inference is complex though. Here, we use the OLS estimator with robust standard errors in parametric regressions, as suggested by Imbens e Lemieux (2008), and local linear regressions with standard errors computed with the *bootstrap*⁷ method (50 replications) in non parametric analyses.

4. Data and methodological issues

The empirical analysis is based on the specification of a standard convergence equation *à la* Barro. The impact of the European regional policy is measured by a Regression Discontinuity Design, where GDP per head (in PPS) is the *forcing variable* and GDP per head growth rate is the *outcome*. We consider the EU-15 regions at level 2 of NUTS 2003 Nomenclature and the analysed period is 1995-2006.

A central point in the analysis is related to the per capita intensity of policy interventions in the different regions. We observed that Cohesion policy expenditure is non limited to the Obj. 1 regions. Actually, also regions interested by other Objectives receive a not negligible amount of money. Therefore the analysis is based on the differences in growth between “hard financed” regions (Obj. 1) and “soft-financed” regions (non-Obj. 1). Considering all the regional policy sources of financing (Structural Funds, Cohesion Fund, National and Private resources) in the two programming periods (1994-1999 and 2000-2006) we identify a threshold of per capita expenditure between Obj. 1 and non-Obj. 1 regions, equal to 1960 euro per head approximately⁸. We excluded non-Obj. 1 regions with a per capita expenditure higher than the threshold. This is true for most of Spanish non-Obj. 1 regions that benefit of the Cohesion Fund and also for regions benefiting of special programmes (like some regions in Finland).

5. Results

We first present some graphical evidence⁹. A simple way to evaluate the effect of the UE regional policy on regional growth is to plot the relation between the outcome variable (per capita GDP growth rate) and the forcing variable (the level of per capita GDP) by regions on either sides of the cutoff point. Figure 1 plots the annual average per capita GDP (in PPS) growth rate in the period 1995-2006 by regions against the per capita GDP level (in PPS), average 1988-1990, standardized with respect to the UE-15 mean value (equal to 100). The evidence is based on the set

⁶ Such a type of problem is considered as being as a standard problem of non parametric regression.

⁷ Bootstrapping is the practice of estimating properties of an estimator (such as mean or variance) by measuring those properties when sampling from an approximating distribution.

⁸ It is the minimum amount of per capita expenditure in Obj. 1 regions.

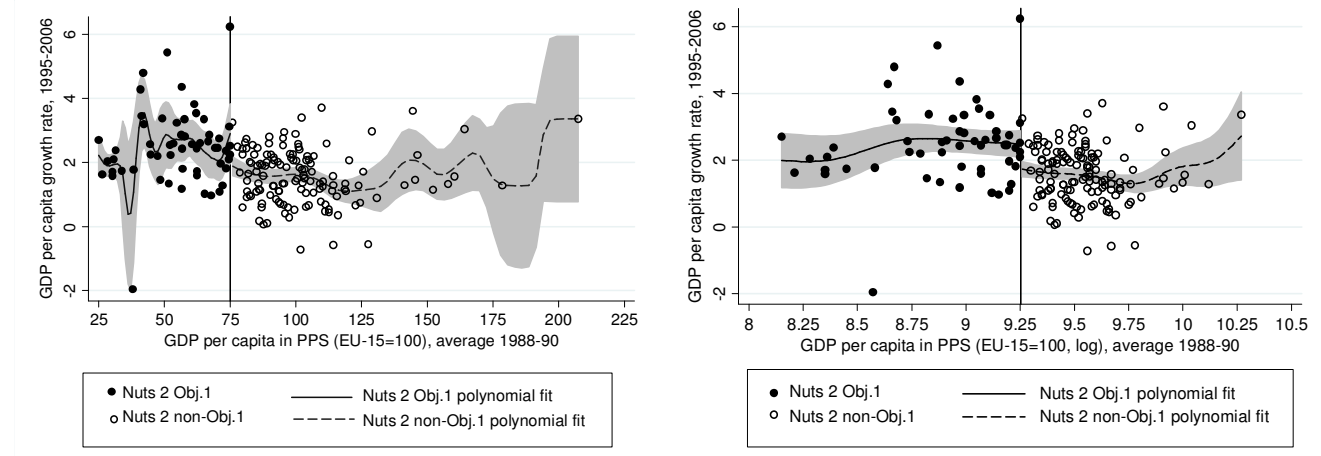
⁹ Tables and figures presented are our data processing on Eurostat and DG Regio data.

of 190 UE-15 NUTS 2 regions. The cut-off line sharply separates treated (in Ob. 1) and not treated (not in Ob. 1) regions. The figure superimposes the fit of a non parametric flexible polynomial regression model, together with the 95% confidence bands.

Fig. 1 – Growth rate and initial level of GDP per capita by UE-15 regions

a) Level in PPS

b) Level in PPS (log)



The Fig. 1 clearly shows that, on average, the Ob. 1 regions grow more than the others. A naïve estimator (the difference of the annual average growth rate between treated and not treated regions) indicates that in the period 1995-2006 the annual per capita growth rate is 0.83 percentage point higher in Ob. 1 regions (the estimated standard error is 0.18). The presence of a distinct but modest discontinuity at the cut-off point is supported by the graph. The non parametric regression line shows a small negative jump moving from the Ob. 1 regions to the not in Ob. 1 regions. The jump is clearer using log.

The parametric approach to the estimation of the treatment effect in the RDD contest has been criticized because the consequences of using an incorrect functional form are in this case more serious. The standard approach now is to use a local linear regression, which minimizes bias (Fan and Gijbels, 1996).

Tab. 1- Non parametric estimates using different bandwidths and kernel types (Local Wald Estimation of the differences between non treated and treated regions. One-side local linear regressions at cut-off are estimated).

Bandwidth	Local Wald Estimation		
	Epanechnikov kernel	Gaussian kernel	Rectangle kernel
15	-0.571 (0.401)	-0.538 (0.506)	-0.251 (0.597)
20	-0.602 (364) *	-0.612 (0.439)	-0.297 (0.507)
21.3 (opt. bw)	-0.638 (0.311) **	-0.628 (0.272) **	-0.392 (0.370)
30	-0.719 (0.284) **	-0.717 (0.392) **	-0.619 (0.352) *
45	-0.886 (0.275) ***	-0.838 (0.375) ***	-0.720 (0.300) **

Note: Bootstrapped standard errors in parentheses. *, **, *** = significant at 10%, 5%, 1% respectively. Bandwidth in measured in PPS (EU-15=100), average 1988-1990.

There are two key issues in implementing a RDD by a local linear regression: the choice of the kernel and the choice of the bandwidth. Respect to the first issue, different kinds of kernel are available. We present our results using three different kernel (Gaussian, Epanechnikov, rectangular). A very delicate part of the analysis is the choice of the bandwidth, that involves finding an optimal balance between precision (more observations are available to estimate the regression) and bias (larger the bandwidth, larger the differences between treated and non treated

regions). We decided to report five estimates as an informal sensitivity test: one using Imbens and Kalyanaraman (2009) formula (the preferred bandwidth), and others increasing or reducing the preferred bandwidth. The standard errors are estimated by a bootstrap procedure (Table 1).

Using the Epanechnikov or the Gaussian kernel and the optimal bandwidth, the effect of the UE regional policy is positive, statistically significant and equal on average to 0.6 percentage points every year. The estimate is the 25% lower than the naïve estimator. Using the rectangular kernel and the same bandwidth the estimate is around 0.4 and not statistically significant, but, if we increase the bandwidth of around the 50%, the effect is equal to 0.6 again and significant at 10%. Increasing the bandwidth, stronger is the discontinuity.

In case of the RD design, valid parametric inference requires a correct specification of the functional form. A more flexible specification involves introducing polynomials in the forcing variable as regressors. The choice of the order of the polynomial can be assessed using some goodness-of fit criteria, like the Akaike information criterion (AIC) of model selection or the Bayesian information criterion (BIC). The adoption of these criteria corresponds to use a generalized cross-validation procedure.

Tab. 2- Parametric estimates using different polynomial fit. Dependent variable: Per capita GDP average annual growth rate period 1995-2006. X=GDPpc in PPS (EU-15=100, average 1988-1990)

	Eq. 1	Eq. 2	Eq. 3	Eq. 4	Eq. 5	Eq. 6	Eq. 7	Eq. 8
	dependent var.: GDP growth rate							
Constant	1.358 (3.33)**	1.571 (21.18)**	1.504 (3.34)**	1.773 (1.95)	4.971 (4.31)**	5.365 (4.73)**	6.391 (1.38)	6.609 (1.42)
X	0.002 (0.52)		0.001 (0.15)	-0.006 (0.37)	-0.059 (3.16)**	-0.066 (3.60)**	-0.091 (0.81)	-0.097 (0.86)
X ²				0.000 (0.52)	0.000 (3.46)**	0.000 (3.96)**	0.000 (0.55)	0.001 (0.6)
X ³							0.000 (0.24)	0.000 (0.3)
Treatment Dummy	1 (4.08)**	0.902 (5.14)**	0.475 (0.61)	0.901 (2.97)**	-2.393 (1.94)	-5.371 (2.77)**	-6.339 (1.34)	-10.964 (1.13)
Treat. Dummy* X			0.008 (0.71)		0.043 (2.55)*	0.158 (2.18)*	0.18 (1.49)	0.475 (0.82)
Treat. Dum.* X ²						-0.001 (1.47)	-0.001 (1.31)	-0.007 (0.61)
Treat. Dum.* X ³								0.000 (0.5)
Observations	190	190	190	190	190	190	190	190
R-squared	0.16	0.15	0.16	0.16	0.18	0.20	0.20	0.20
RMSE	0.974	0.972	0.974	0.975	0.962	0.957	0.960	0.961
AIC	532.1	530.4	533.3	533.7	529.4	528.5	530.4	531.8
BIC	541.8	536.9	546.3	546.7	545.7	547.9	553.2	557.8

Robust standard errors in parentheses in parentheses. * significant at 5% level; ** significant at 1% level

The results of OLS estimates with heteroskedasticity-robust standard errors on the full sample, adding different polynomials, are presented in Table 2. The BIC criterion chooses the simplest specification, just a comparisons of annual average growth rate on the two sides of the cut-off point. The effect is positive, statistically significant, equal to 0.9 percentage point per year, higher than in the non parametric estimation. The AIC criterion chooses a specification with a linear and a quadratic term, and the jump is again statistically significant.

6. Robustness proofs

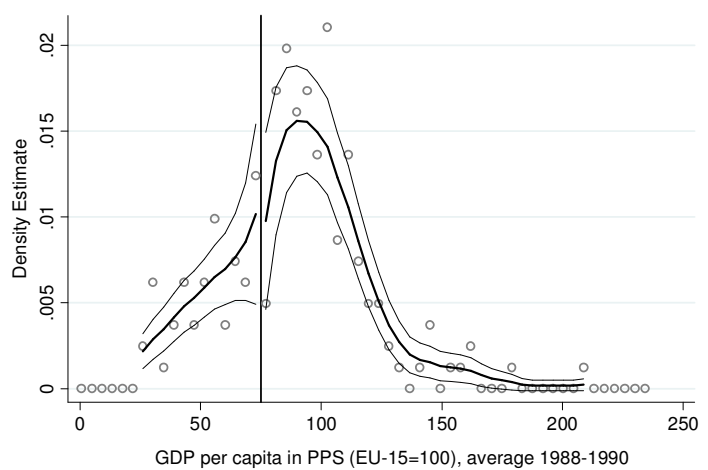
Following Imbens and Lemieux (2008), we assess the robustness of our results employing various specification tests:

- testing for possible discontinuities in the conditional density of the forcing variable (the level of per capita GDP);
- taking whether the outcome (the regional annual growth rate) is discontinuous not only at the cut-off but also at other values of the forcing variable;
- considering the presence of a spatial correlation in the regional growth rates.

The evidence of a jump in the conditional density of the forcing variable can be a test of the imprecision of control over the forcing variable, as suggested in McCrary (2008): if there is some

degree of sorting of the regions around the threshold, the appropriateness of the RDD in this contest is dubious. A formal test of manipulation related to continuity of the forcing variable density function is presented in McCrary (2008). We present here in Figure 2 a kernel estimate of the density function of the regional GDP per capita with the 95% confidence bands, following McCrary (2008). The weak discontinuity around the cut-off point is not statistically significant.

Fig. 2 - Estimated density of the forcing variable at the cut-off (per capita GDP, average 1988-1990)



Another robustness test verifies that there are no extra jumps in the levels of the outcome where no hypothesized cut-off exists. The approach used here consists of testing for a zero effect in different points of the forcing variables. We tested the effects using different kernels and bandwidth. Some discontinuities are captured only around the values from 75 to 80, however close to the hypothesized cut-off.

Finally, we tested that the presence of a spatial correlation does not affect the results. The residuals of the parametric model present a clear correlation across neighbours. We capture the spatial correlation by a spatial error model and by a spatial lag model. Even if the selected specification (using the AIC and BIC criteria) is different between the two models, the estimates confirm our previous results.

7. Conclusions

The results show that the policy has a positive, even if moderate, impact on regional growth. The per capita GDP of the “treated” regions (regions in Obj. 1) grew on yearly average in the period 1995-2006 0.8 percentage points more than in the non treated regions. Our results suggest that the effect of the policy is equal to 0.6 percentage point if measured by a non parametric model, 0.8-0.9 percentage point if measured by a parametric model. The different weight given to the observations closer to the cut-off point (higher for the non parametric model) explains the differences between the two approaches. It follows that the most part of the larger growth of Obj. 1 regions in the period is attributed to the Regional policy. The estimate are statistical significant and robust to different model specifications and to error spatial correlation.

The presence of a (slow) convergence process across UE regions in the last twenty years is, in our estimates, basically ascribed to the regional policy action. In absence of the policy the integration of the Europe would be slower, with higher economic and social disparities.

The results support the effectiveness of the policy. However, the causal effects are modest, lower than the estimates (1.8 per cent) presented in the recent paper of Becker and al. (2008). For that reason the efficiency of the UE Regional Policy remains an open problem.

There are two aspects that are left for future research: a methodological one, related to the use of a fuzzy RDD, in order to take into account the possibility of a different intensity of regional support by Structural Funds; an empirical one, that consider the possibility of a different impact of the Regional policy in the Cohesion Fund countries with respect to the non-Cohesion ones.

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