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

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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 policy's contribution to regional economic growth. However, so far no consensus has been reached on the effectiveness of Cohesion policy, 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 effectiveness of UE Regional Policy, using a counterfactual method - the regression discontinuity design (henceforth RDD). We exploit the allocation rule of regional UE transfer: regions with a per capita GDP level below 75% of the EU average receive a huge amount of UE structural funds transfers. The sharp RDD is based to the jump in the probability of EU transfer receipt at the 75% cut-off point. Comparing the economic scenario arising under policy interventions with a 'counterfactual' situation - what would have happened if the policies were not implemented - we identify the economic effect of European regional interventions and show that they are positive and statistically significant. The most part of the larger growth of Obj. 1 regions in the period 1995-2006 can be attributed to Regional Policy.

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

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Introduction

The purpose of this paper is to assess the effectiveness of Regional policy, using a reliable and comparable dataset and a counterfactual method - the regression discontinuity design (henceforth RDD) - to evaluate the policy impact on economic growth.

Regional policy - or Cohesion policy - is one of the key axes of EU integration, together with single market and monetary union. Its objectives are anchored in Article 158 of the Treaty establishing the European Community, which states that: "In order to promote its overall harmonious development, the Community shall develop and pursue its actions leading to the strengthening of its economic and social cohesion. In particular, the Community shall aim at reducing disparities between the levels of development of the various regions and the backwardness of the least favoured regions or islands, including rural areas" [1].

In the period 2007-2013, a relevant share of the EU budget – around 36 per cent (€347 billion) – is intended for this purpose. The majority of this funding targets the most disadvantaged European regions, identified on the basis of EU statistical indicators and criteria. Although low as a percentage of total EU GNI (0,38 per cent), still Cohesion policy represents an important share of resources devoted to public investment policies in the least prosperous regions and Member States of the Union[2].

Given the increasing share of the EU budget devoted to Regional policy since the mid-1970's[3], 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,

[1] The Lisbon Treaty, which has yet to be ratified by all Member States, modified the text referring to economic, social and territorial cohesion.
[2] In the period 2000-2006, Regional policy commitments amounted, on average, to an estimated 60 per cent of total public capital expenditure in Portugal, 48 per cent in Greece and 24 per cent in Spain. See European Commission (2007).
[3] Since the establishment of the European Regional Development Fund (ERDF) in 1975, financial resources for Cohesion policy have progressively increased, from a mere 5 per cent of the total Community budget (1.3 billions European Unit of Account) to around 36 per cent over the present 2017-2013 period. See Manzella and Mendez (2009).

2008).

This is 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 happened if the policies were not implemented[4]. The counterfactual approaches 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.

The paper is structured as follows. Section 2 summarises the literature and available empirical evidence on the effects of Regional policy. Section 3 describes the institutional design of EU Regional policy. The evaluation method is discussed in Section 4, followed by a presentation of the

[4] 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).

database in Section 5. The results of the empirical analysis are discussed in section 6, while section 7 assesses the robustness of the results. Finally, we briefly conclude and define some path for future research.

1. Literature review

Since the establishment of the European Regional Development Fund (ERDF) in 1975, the reduction of regional disparities - the Treaty general mission - has often been measured in terms of GDP per head. The limits of this perspective is that it may not be capturing the different dimensions of well-being, providing a distorted view of regional disparities in terms of people's quality of life[5]. Indeed, convergence in GDP per head has become a major aspect in assessing the effectiveness of EU Regional policy, disregarding the more general goals of the Treaty to "*promote economic and social progress as well as a high level of employment, and to achieve balanced and sustainable development through the strengthening of economic and social cohesion* ..." (Article 2)[6]. These considerations, however, do not suggest dismissing GDP or GDP per capita measures, as they continue to provide relevant information in monitoring economic activity, particularly at territorial level where limitations in the cross-country comparability of statistics affect the comparison among regions.

Considering the available empirical evidence on the effectiveness of Regional policy, results are not unanimous depending on model specification, statistical methodologies and observations (such as geographical areas and reference period). In particular, analyses based on econometric studies do not provide a consistent picture on the effects of Cohesion policy. We can therefore classify empirical analysis in three groups depending on their results: a first group of studies finding a positive impact of Cohesion policy on growth and convergence, a second group finding mix results, and a third group according to which the effects of Regional policy are not significant or even negative.

Among the first group of studies (de la Fuente and Vives, 1995) estimate a growth model that includes public and human capital, and using Spanish regional data for the 1980-90 show that the potential impact of public investment in infrastructure and education on productivity growth is considerable. Hence, supply-side Regional policies have significant effects on income growth and convergence, their impact on regional disparities depending on the overall amount of resources devoted to them. Cappelen *et al.* (2003), using a pooled cross-country time-series dataset for the period 1980-1997, show that Cohesion policy has a significant and positive impact on the growth performance of European regions. However, they also stress that the economic impact is stronger in more developed environments, suggesting the need to accompany regional support with national policies that facilitate structural change and increase R&D capabilities in poorer regions. Finally, in

[5] On the limits of GDP as an indicator of economic performance and social progress see the recent report by Stiglitz, Sen and Fitoussi (2009).
[6] See Monfort (2009).

a study by Beugelsdijk and Eijffinger (2005), using a panel regression of the EU-15 countries for the period 1995–2001, a positive relationship between (lagged) Structural Funds expenditure and GDP growth at the national level is found.

A positive impact of regional policy is also found by the literature on simulation models, initiated by the so called HERMES model in 1990s. Performed only for Ireland to analyse medium-term supply side shocks in the 1970s and 1980s (Bradley, Fitz Gerald and Kearney, 1992), in HERMES the cohesion support for 1989-1993 raised Irish GDP with 2.6 percent by the year 2000, whereas the impact on GDP per capita turned out to be much smaller. On the basis of HERMES model, which was considered by the authors themselves too rich and disaggregated for being viewed as a well-suited policy evaluation tool, it was developed the HERMIN model for Ireland, Spain, Greece and Portugal[7]. Both the programming periods 1994-1999 and 2000-2006 have been considered (Bradley *et al.*, 2001). As far as the analysis of the Funds impact over the period from 1994 to 1999 (which ignores both the carry-over impacts of Structural Funds 1989-93, and the successive Structural Funds aid for the period 2000- 2006), it emerges that the aggregate impacts on the level of GDP in Portugal are quite large and over 4.5 percent with respect to "no- Structural Funds" benchmark in 1999, in Greece and Spain about 2 percent, while Ireland they are at almost 3 percent. Further, from an evaluation performed for the eastern Germany, the Funds impacts over the period 1994-1999 turned out to be equal to 4 percent. Simulations for the successive programming period 2000-2006 still confirm the enhancing growth role of these Funds (Bradley *et al.*, 2003)[8]. A further analysis on the basis of HERMIN model has been conducted by Fitz Gerald (2004). Quite interestingly, it emerges from his work that although the amount of Funds employed for sustaining cohesion results to be low with respect to the needs of countries, still the cohesion policy seems to play a significant role in enhancing convergence. Finally, a positive impact of Funds is found by QUEST II, a forward-looking model of the EC that focuses on the demand side (Röeger, 1996) and assumes that the macroeconomic impact of the Funds takes place as an increase in the public capital stock, which in turn affects a neo-classical production function. This model has been adopted for ex-post evaluation of the programming period 1983-1993 and 1994-1999, and for ex-ante evaluation of the programming period 2000-2006[9]. It is worth noting that mainly because of the forward-looking expectations and the endogenous determination of real interest and exchange rates (which are exogenously given in HERMIN), the results provided by the QUEST II simulations for

[7] Hermes embeds 10 sectors and more than 700 equations, while HERMIN is just a four-sector model. Detailed results of the resulting simulations are published in each of the Objective 1 Community Support Frameworks 2000-06 ("CSF") for the programming of Structural Funds in these four countries.

[8] Due to the specific characteristics of eastern Germany, the short time series available and the strong dependence on the western German economy, this version of HERMIN model is simplified with respect to the model used for the above mentioned simulations.

[9] See Roeger (1996), EC (2000), and Objective 1 CSF for Spain, Ireland, Greece and Portugal.

Greece, Spain Ireland and Portugal for real GDP are low compared to the HERMIN simulations.

Others studies find only conditional effectiveness of Regional policy or mixed evidence. Ederveen *et al.* (2002), observing EU-12 countries in the period 1960-1995 find that Cohesion policy fosters economic growth in lagging Member States conditional on the openness of the economy. At the regional level, for a sample of 183 NUTS-2 regions between 1981 and 1996, the estimated impact of cohesion policy on economic growth is positive and significant if one presupposes that each region grows towards its own steady state level of GDP per capita (so that differences will persist). The estimated impact is, however, negligible or even negative if one assumes that regions will converge to the same steady state level of GDP per capita (so that differences will disappear in the long run). Ederveen *et al.* (2006), using a dynamic panel specification with data on 13 EU-countries covering seven five-year periods from 1960–1965 through 1990–1995, attempt to assess the effectiveness of Structural Funds and whether this is conditioned by the "quality of institutions" proxied by quantitative measures of corruption, inflation or openness to trade. They show that when institutional quality is explicitly taken into account, the impact of Structural Funds on regional growth is positive and significant: economies with good institutional quality benefit from the funds.

Finally, a further strand of evaluations of the impact of the Funds on growth and convergence tends to be quite pessimistic. Canova and Marcet (1995) and Fagerberg and Verspagen (1996), for example, do not find any significant impact of the Funds in their convergence regressions. The same result holds for Vanhoudt (2000), looking at the impact of public investment (national and European) in EU regions. Analysing different measures of dispersion at the regional level for a set of 185 NUTS 2 regions during the period 1980–1996, Boldrin and Canova (2001) do not find convergence of regional per capita incomes. Not even signs of accelerating growth rates in less developed regions appear. Thus, they reject the hypothesis of a positive impact of Structural Funds expenditure.

2. The EU Cohesion Policy

In 1986 the Single European Act of the European Community expressed the objectives of economic and social cohesion for the first time. These objectives were adopted in 1998 by the first regulation giving birth to Cohesion Policy. The need for a European regional development policy has grown in parallel with the European integration process. This policy has in fact always been perceived as an instrument able to contain the risk that the economic development sped up by the creation of a single market among very heterogeneous member states could have exacerbated existing inequalities. In this perspective, the Cohesion Policy is meant to help weaker economies to fill the gap with the rest of the EU and does so by funding development programmes in regions that lag behind in production per capita, whose industry are losing competitiveness or facing high unemployment rates. Developing infrastructure network, supporting enterprises, investing in education, research and innovation activities as well as in environmental protection programmes, are all examples of regional policy initiatives[10,11].

Cohesion Policy represents now the second largest policy area in the EU budget after the Common Agricultural Policy (CAP). In the current programming period 2007-2013, it accounts for 347.4 billion euros that correspond to 35.7 per cent of the total EU budget. This figure is significantly higher than the initial percentage of 6.2 per cent of the EU budget in 1975, when the European Regional Development Fund was created, and with respect to the value of 25 per cent of the EU budget in 1988, when a comprehensive regional development policy system was put into action.

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. This diversity is reflected in the definition of the priority Objectives of the policy which allow to identify both the scope of the interventions and the territorial eligibility of each European region.

[10] A significant shift in investment priorities has been made with the 2007-2013 programming period. A quarter of resources are in fact now earmarked for research and innovation and about 30 per cent for environmental infrastructure and measures combating climate change.

[11] Cohesion Policy includes different financial instruments that allow to fulfil the territorial Objectives defined in the regulation, each of them addressing the need of a specific territorial area. Two of the above mentioned financial instruments fall under the Structural Funds programme. The first is the European Regional Development Fund (ERDF), which supports programmes for infrastructure development, job-creating investment, research, innovation as well as environmental protection activities. The second, the European Social Fund (ESF), is aimed at increasing the adaptability of workers and enterprises, enhancing the access to employment as well as the participation in the labour market, thus reinforcing social inclusion. A third additional financial instrument, the Cohesion Fund, goes in favour of member states with a gross national income of less than 90 per cent of the Community average. Originally, this fund was created to help four countries (Ireland, Greece, Portugal and Spain) meet the criteria for joining the single currency. Now it covers the new member states as well as Greece and Portugal, while Spain is still eligible on a transitional basis.

After several adjustments made during the three programming periods completed so far (1989-93, 1994-99, 2000-06), the current Cohesion Policy strategy identifies three territorial Objectives (Convergence, Regional Competitiveness and Employment, European Territorial Cooperation). However in the period of our analysis the priorities were named Objective 1, 2 and 3, described as follows.

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).

All other EU regions were instead covered by Objectives 2 and 3 of previous programming periods that now are merged in the Regional Competitiveness and Employment Objective. This is the second highest level of funding available from the EU. Its aim is to strengthen, competitiveness, attractiveness as well as employment in regions. At present, it concerns 168 regions, for a total of 314 million inhabitants, included the regions that went out from Objective 1 territorial level at the end of the 2000-2006 programming period and that are currently receiving assistance on a transitional basis ("phasing in" regions in the 2007-2013 regulation). Moreover, Cohesion Policy has always provided assistance for a certain period of time to regions that have improved their economic performance and have been able to move out from Objective 1 territorial level (the "phasing-out" programme)[12].

Different territorial Objectives correspond to different concentration of funds, meaning a different amount of per capita Cohesion policy expenditure by regions. Even though Cohesion Policy has always aimed at solving different problems of economic decline in specific areas (areas with industrial decline, areas combating long-term unemployment, facing rural underdevelopment, or suffering problem of urbanization, etc.), supporting the least developed regions has always been its major priority. The definition of "least developed regions" through the adoption of the rule of 75 per cent of per capita GDP with respect to the EU average, as a threshold below which each

[12] The third Objective, the European Territorial Cooperation Objective, has been introduced in the 2007-2013 programming period, but it is based on the past experience of Interreg initiatives. It aims at reinforcing cooperation at cross border, trans-national and inter-regional level. It complements the other two Objectives mentioned above as the eligible regions are also eligible for the Convergence and Regional Competitiveness and Employment Objectives.

European region is entitled to receive assistance within the Objective 1 territorial level, has been kept unchanged during the different programming periods. Regions that have complied with this rule have always been eligible to receive most of the payment.

Despite the adoption of the rule of "75 per cent", the procedure of funds allocation has not always been automatically determined and transparent. This is due to the political negotiations among member states that have often influenced the planning of the EU budget. Consequently, in the past programming periods a number of member states have been entitled to receive assistance within the "Objective 1" framework for their entire territory, even if some regions were not fully in compliance with the criterion set in the regulation. In spite of this, our analysis shows that in the period considered (1989-2005), Objective 1 regions have however received, on average, a larger amount of funds than all other EU regions involved in the Cohesion Policy.

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. It is worthy underlying the distinction between two different RD designs considered in the literature - the sharp design and the fuzzy design. In the sharp design, the treatment assignment is a deterministic function of the forcing variable, while in the fuzzy design the treatment is based on a stochastic function. In our paper we adopt the sharp design.

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. 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)[13].

Although, it only identifies treatment effects locally at the cut-off-point, it is worth stressing that 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

[13] 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.

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 EU[14]. In our analysis, participants are assumed to be European regions: precisely 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 EU Structural funds[15].

The use of RDD for assessing the impact of EU regional policy is however complex, for several reasons. First, the limited number of observations near the threshold determines a trade-off between the interval extension around the cut-off point and the statistical precision of estimates.

Second, we are faced with a high variability of regional growth with respect to the initial level of GDP per capita, due to the numerous factors which influence the outcome[16]. In this case, the limited number of observations near the cut-off point might produce a group of regions with features that differ markedly from those of non beneficiaries, hindering the accuracy of estimates.

Given the large amount observations very close to the threshold, the idea is that on average, regions to the left and the right of the cut-off point does not systematically differ in their main features except that those to the left of the 75 percent threshold receive EU structural funds while those to the right do not. Also, through comparing the average regional GDP growth of regions receiving EU funds and non beneficiaries at the margin we can control for confounding factors and identify the average policy effect locally at the threshold.

Let us briefly describe below the model at the basis of our work[17]. 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.

[14] See Lee and Lemieux (2009) for a survey of the areas of applied economic research that have used the RDD.
[15] We refer the interested reader to Imbens and Lemieux (2007) for details.
[16] Considering running an OLS regression on a constant, the initial level of per capita GDP and a dummy for the treatment: it will explain 13 percent of the outcome.
[17] The basic framework is closely related to Imbens and Lemieux (2007), to which the reader is refereed for further details.

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:

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

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[18]:

$W_i = 1\{X_i \leq c\}$ con 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)

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

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

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

Of course, it is not possible to observe for each region *i* both the values $Y_i(1)$ and $Y_i(0)$, neither to use a matching method for comparing region *i* with a similar one (i.e. with similar values for all covariates). This implies comparing the average value of regional growth for treated regions and non treated regions at $X=c$.

By design, there are no units with X_i=c for whom we observe $Y_i(0)$. Thus, we exploit the fact that we observe units with covariate values arbitrarily close to c. In order to justify this averaging we make a smoothness assumption (i.e. that the relation between X_i and Y_i is smooth around c), known in the literature as "continuity of conditional regression functions".

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

[18] This is a case of "sharp design", as the treatment (receiving EU funds) only depends on the level of X_i.

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:

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

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:

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

Accordingly, the average effect writes as:

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

Given this, we need to estimate two limits, approaching c from right and left[19]. 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*[20] method (50 replications) in non parametric analyses. Finally, we use the following tests:

1) the presence of a discontinuity in the density function of X at $X = c$, which could signal the existence of manipulations in the forcing variable by the units;
2) the presence of other discontinuities in the forcing variables, which will make weaker the assumption that the discontinuity of the outcome at $X = c$ is an effect of the treatment;
3) the presence of variables with a discontinuity at $X = c$ not affected by the treatment, which could determine the discontinuity of the outcome Y at $X = c$.

[19] Such a type of problem is considered as being as a standard problem of non parametric regression.
[20] 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.

4. Data and methodological issues

The counterfactual approach has been rarely adopted in the assessment of the impact of EU regional policy. The main difficulty is to isolate the effects of the policy from those of several external confounding factors, i.e. to identify the appropriate counterfactual, that is the outcome in terms of economic growth that beneficiary regions would have reached without EU funds.

The RDD allows the assessment of policy effects without the use of complex econometric models. With this method, regions around the 75 per cent cut-off point are more comparable than regions away from the threshold. Ideally, with many observations very close to the threshold, on average, regions to the left and the right of the cut-off point do not systematically differ in their characteristics except that those to the left of the 75 percent threshold receive EU structural funds and those to the right do not. In a neighbourhood of the threshold, the treatment is assigned as in a randomised experiment. The comparison of average regional GDP growth between regions receiving EU funds and non beneficiaries at the margin allows to control for confounding factors and to assess the average policy effect locally at the threshold.

In this paper we will present different analyses, using parametric and non parametric estimators, modifying a number of key characteristics (e.g. specification, sample, bandwidth, kernel function). Moreover, different tests will be presented as suggested by Lee and Lemieux (2009) and Imbens and Lemieux (2008).

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, because data at a lower territorial level (i.e. NUTS level 3) are not available[21]. The period that we have considered for analyzing the regional policy impact is strictly related to the 1988 reform of the Structural Funds, when the amount of financial resources dedicated to the Cohesion policy increased considerably. The poor availability of data (in terms of regional policy expenditure and GDP regional growth[22]) for the programming period 1989-1993 has forced us to limit the analysis to the years 1995-2006, considering the two programming

[21] It is not easy to collect statistics with respect to the GDP growth. As a matter of fact, even though the regional economic statistics have been recently improved, regional GDP values in volume are not available in a unique and comparable source. On the other hand, the territorial level that the Cohesion policy refers to is NUTS 2. Disposing of less disaggregated regions, that is using a lower number of statistical units, does not mean working with inaccurate data, but only increase the probability of inconsistent estimates.

[22] Data on regional GDP in volume are not directly available. To calculate the average GDP per capita growth rate we dispose of GDP growth rate for the years following the 2000 and, to complete the necessary series, we received the estimates GDP growth rate for the period 1995-2000 by DG Regio.

periods 1994-1999 and 2000-2006. Moreover, the analysis uses also data on GDP per head for the years 1988-1990. Objective 1 regions are NUTS 2 regions whose per capita GDP, measured in purchasing power parities and calculated on the basis of Community figures for the last three years available, is less than 75% of the Community average. NUTS 2 regions included in Objective 1 in the two programming periods interested by the analysis, 1994-1999 and 2000-2006, are defined as "treated" regions. As we explained before, the last three years available to define Objective 1 regions in the programming period 1994-1999 were years 1988-89-90. The averages of these three GDP per capita values (in PPS at NUTS level 2) represent our *forcing variable* values.

The NUTS 2003 Nomenclature counts 213 NUTS 2 regions, classified in this study as Obj. 1 regions for 71 cases and as non-Obj. 1 regions for the remaining 142 cases. We decided to exclude in the estimates 14 NUTS 2 among the Obj. 1 regions and 9 NUTS 2 among the non-Obj. 1 regions, for a total of NUTS 2 regions analyzed equal to 190. There are several causes that determined this choice:

1. we eliminate regions that are not in the Obj. 1 for the overall period considered. They basically are regions in Obj. 1 for the period 2000-2006, but not in the period 1994-1999[23];
2. regions only partially in Obj. 1 for the period 2000-2006[24];
3. we eliminated NUTS 2 regions[25] whose per capita GDP average in the period 1988-1990 was above than 75% of the Community average, included in Objective 1 for political reasons.

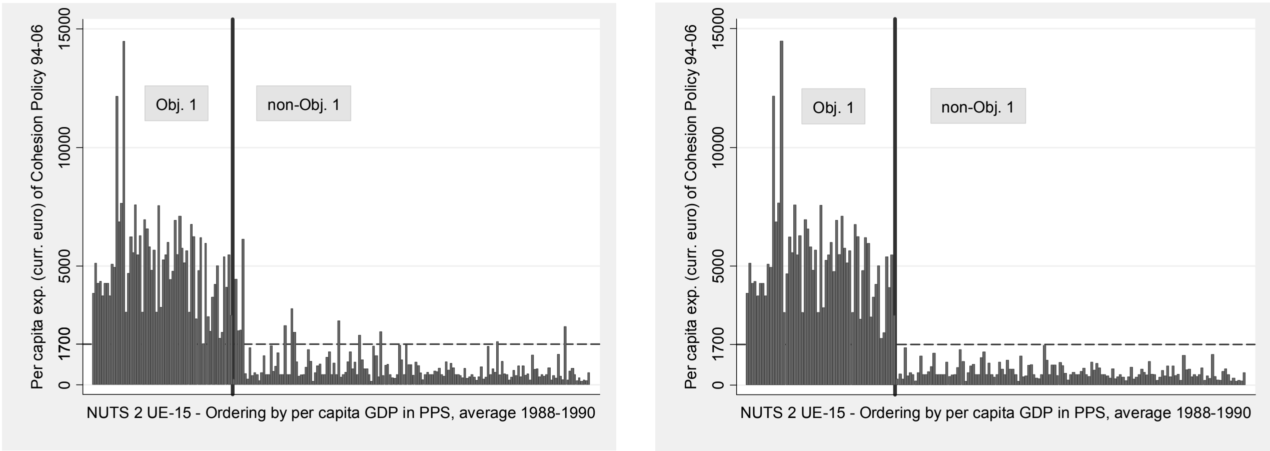
A central point in the analysis is related to the per capita intensity of policy interventions in the different regions. We observed that Cohesion policy expenditure is non limited to the Obj. 1 regions. Actually, also regions interested by other Objectives receive a not negligible amount of money. Therefore 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 approximately[26]. 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 beneficing of special programmes (like some regions in Finland).

[23] These NUTS 2 regions are: Burgenland (AT), Itä-Suomi (FI), South Yorkshire (UK), Cornwall and Isles of Scilly (UK), West Wales and The Valleys (UK).
[24] They are: Länsi-Suomi (FI), Pohjois-Suomi (FI), Norra Mellansverige (SE), Mellersta Norrland (SE), Övre Norrland (SE);
[25] Prov. Hainaut (BE), Corse (FR), Molise (IT), Lisboa (PT).
[26] It is the minimum amount of per capita expenditure in Obj. 1 regions.

Fig. 5.1 – Cohesion policy per capita expenditure (1994-2006)

a. Complete NUTS 2 Nomenclature (213 regions) b. NUTS 2 for RDD (190 regions)



Source: data processing on DG Regio data.

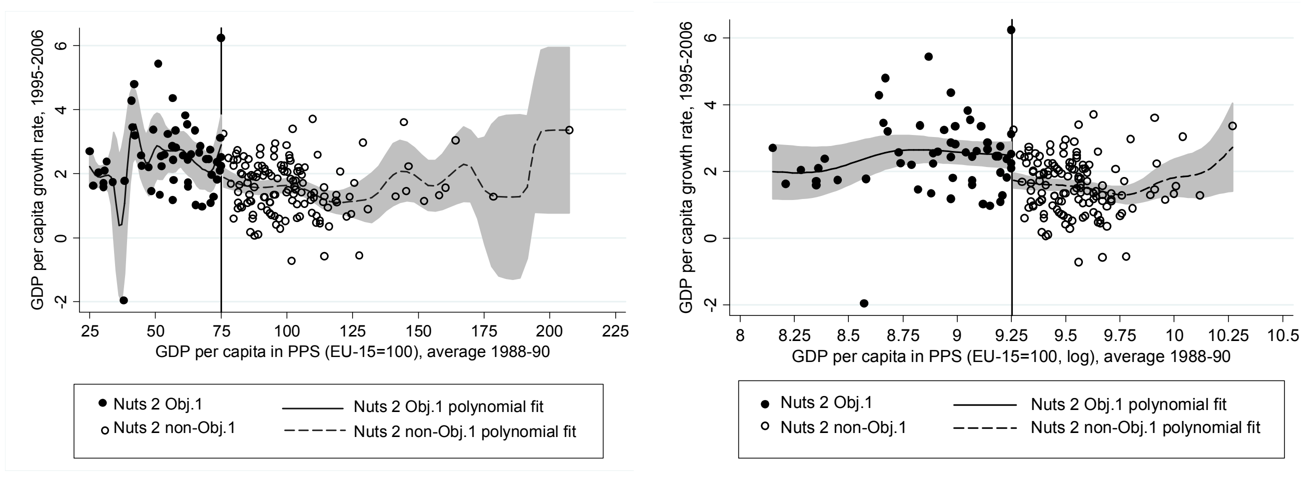
The results of our data netting are presented in Fig. 5.1, where the treated and the not treated groups are clearly separated. In this situation we can carry out a quasi-experimental design as is the RDD. The evaluation of treatment effect provides to identify the presence of a "jump" in terms of growth in correspondence of the EU 75% per capita GDP, the Obj. 1 eligibility threshold.

5. Results

We first present some graphical evidence[27]. 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. If there is no visual evidence of a discontinuity in the graph, it is unlikely the more sophisticated regression methods will yield a significant policy effect (Lee and Lemieux, 2009). Figure 6.1 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 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. 6.1 – Growth rate and initial level of GDP per capita by UE-15 regions

a) Level in PPS **b) Level in PPS (log)**



The Fig. 6.1 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. Finally the figure indicates that the relation between the outcome and the

[27] Tables and figures presented are our data processing on Eurostat and DG Regio data.

forcing variable is weak, and a simple horizontal line parallel to the x-axis can adequately approximates it. The descriptive evidence, using a graphical representation, suggests that there are discontinuities in the per capita GDP growth rate between treated and not treated regions, but the effects are moderate, and therefore not easy to detect.

The parametric approach to the estimation of the treatment effect in the RDD contest has been criticize because the consequences of using an incorrect functional form are in this case more serious. The misspecification of the functional form can generate a bias in the treatment effect (Lee and Lemieux, 2009). The paper that recently has attracted again the attention of economists and statisticians on this design proposes the use of a nonparametric regression method (Hahn *et al.*, 2001). The standard approach is to use a local linear regression, which minimizes bias (Fan and Gijbels, 1996).

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.

Different kinds of kernel are available. It has been shown in the statistics literature that a triangular kernel is optimal for estimating local linear regressions at the boundary (Fan and Gijbels, 1996), and therefore has good properties in the RD context. The use of a rectangular kernel amounts to estimating a standard regression over a window given by the bandwidth on both sides of the cutoff point. However, while other kernels (Gaussian, Epanechnikov, etc.) could also be used, Lee and Lemieux (2009) argue that the choice of kernel typically has little impact in practice (see also Imbens and Lemieux, 2009). The statement is basically true also in our case. We present our results using three different kernel (Gaussian, Epanechnikov, rectangular).

A very delicate part of the analysis is the choice of the bandwidth. In a non-parametric RDD estimation it 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). Smaller bandwidths are feasible if the number of observation is reasonably high. There are several rule-of-thumb bandwidth choosers, but none is completely reliable. A recent contribution of Imbens and Kalyanaraman (2009) presents a data-dependent method for choosing an asymptotically optimal bandwidth in the case of a RDD.

Imbens and Kalyanaraman (2009) define an optimal, data dependent, bandwidth choice rule integrating a modified Silverman bandwidth rule:

$$\tilde{h}_{opt} = C_k \left(\frac{2\hat{\sigma}^2(c)/\hat{f}(c)}{\left(\hat{m}_+^{(2)}(c) - \hat{m}_-^{(2)}(c)\right)^2 + \left(\hat{r}_+ + \hat{r}_-\right)} \right)^{1/5} N^{-1/5} \tag{5.1}$$

where

$\hat{\sigma}^2(c)$ is the conditional variance,

$\hat{f}(c)$ is the estimation of density at cut-off point,

C_k is a constant that depends by the used *kernel*,

N is the number of observations,

$\hat{m}_+^{(2)}(c)$ and $\hat{m}_-^{(2)}(c)$ are the second derivates obtained fitting the observations in *(c)* with $X_i \in [c, c+h]$,

$\hat{r}_+$ e $\hat{r}_-$ are regularizations terms.

However, different bandwidth choices are likely to produce different estimates. We decided to report five estimates as an informal sensitivity test: one using Imbens and Kalyanaraman formula (the preferred bandwidth), and others increasing or reducing the preferred bandwidth. The standard errors are estimated by a bootstrap procedure. The results are presented in Table 6.1.

Tab. 6.1- 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).

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

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. The reason is clearly exposed in ure A.1a, A.1b and A.1c in the Appendix: wider the bandwidth, higher the smoothness, lower the impact of some erratic observations close to the cut-off line. In this case the rectangular kernel needs a larger window for smoothing these observations.

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 parametric approach can integrate the non parametric one, both assessing the robustness of the RD estimates of the treatment effect. Lee and Lemieux (2009) argue that, in the case of polynomial regressions, the equivalent to bandwidth choice in the non parametric regression is the choice of the order of the polynomial regressions. Therefore it is advisable to try and report a number of specifications to see to what extent the results are sensitive to the order of the polynomial. The choice of the order of the polynomial can be assessed using some goodness-of fit criteria, like the well known Akaike information criterion (AIC) of model selection or the Bayesian information criterion (BIC), where the penalty for additional parameters is stronger than that of the AIC. The adoption of these criteria corresponds to use a generalized cross-validation procedure.

Tab. 6.2- 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	1.571	1.504	1.773	4.971	5.365	6.391	6.609
	(3.33)**	(21.18)**	(3.34)**	(1.95)	(4.31)**	(4.73)**	(1.38)	(1.42)
X	0.002		0.001	-0.006	-0.059	-0.066	-0.091	-0.097
	(0.52)		(0.15)	(0.37)	(3.16)**	(3.60)**	(0.81)	(0.86)
X^2				0.000	0.000	0.000	0.000	0.001
				(0.52)	(3.46)**	(3.96)**	(0.55)	(0.6)
X^3							0.000	0.000
							(0.24)	(0.3)
Treatment Dummy	1	0.902	0.475	0.901	-2.393	-5.371	-6.339	-10.964
	(4.08)**	(5.14)**	(0.61)	(2.97)**	(1.94)	(2.77)**	(1.34)	(1.13)
Treat. Dummy* X			0.008		0.043	0.158	0.18	0.475
			(0.71)		(2.55)*	(2.18)*	(1.49)	(0.82)
Treat. Dum.* X^2						-0.001	-0.001	-0.007
						(1.47)	(1.31)	(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 6.2. 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.

In the spirit of the RDD we also estimated the treatment effect in a restricted sample around the cut-off point. We excluded the lower quarter (in term of initial level of per capita GDP) for the treated regions and the higher quarter for the non treated regions. Our sample has been reduced from 190 to 143 regions. In this case both the criteria choose the simplest specification (Table 6.3). The treatment effect is positive, statistically significant and equal to 0.9 percentage point per year.

Tab 6.3 - Parametric estimates using different polynomial fit: restricted sample. 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	2.121	1.645	2.11	2.757	12.483	15.552	38.84	169.706
	(2.56)*	(20.42)**	(2.40)*	(1.14)	(1.37)	(1.52)	(0.39)	(1.74)
X	-0.005		-0.005	-0.021	-0.229	-0.295	-1.049	-5.286
	(0.57		(0.53)	(0.39)	(1.17)	(1.33)	(0.33)	(1.66)
X^2				0.000	0.001	0.002	0.010	0.055
				(0.31)	(1.14)	(1.31)	(0.28)	(1.6)
X^3							0.000	0.000
							(0.23)	(1.53)
Treatment Dummy	0.741	0.903	0.768	0.706	-5.233	-11.268	-28.511	-262.436
	(2.13)*	(4.99)**	(0.52)	(1.77)	(0.92)	(0.9)	(0.38)	(2.37)*
Treat. Dummy* X			0		0.077	0.242	0.687	10.201
			(0.02)		(1.02)	(0.73)	(0.35)	(2.43)*
Treat. Dum.* X^2						-0.001	-0.004	-0.138
						(0.49)	(0.31)	(2.38)*
Treat. Dum.* X^3								0.001
								(2.23)*
Observations	143	143	143	143	143	143	143	143
R-squared	0.18	0.18	0.18	0.18	0.19	0.19	0.19	0.23
RMSE	0.892	0.890	0.896	0.895	0.894	0.896	0.899	0.881
AIC	376.2	374.6	378.2	378.1	378.7	380.4	382.3	377.4
BIC	385.1	380.5	390.1	389.9	393.5	398.2	403.1	401.1

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

The results are similar if the model is specified in log, closer to a standard convergence equation *à la Barro* (see Table A.2 for the full sample and Table A.3 for the restricted sample in the Appendix).

6. Robustness proofs

Following Imbens and Lemieux (2009), we assess the robustness of our results employing various specification tests:

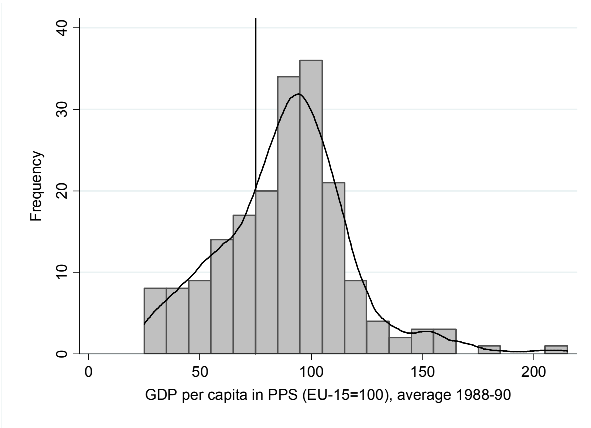
a) Testing for possible discontinuities in the conditional density of the forcing variable (the level of per capita GDP);
b) Looking whether the outcome (the regional annual growth rate) is discontinuous not only at the cut-off but also at other values of the forcing variable;
c) Looking at possible jumps in the value of other exogenous covariates at the cut-off point
d) Considering the presence of a spatial correlation in the regional growth rates

Testing for discontinuities in the conditional density of the forcing variable is related to the possibility of manipulations of the forcing variable. If regions can manipulate the forcing variable in order to obtain desirable treatment assignments (that is, in our case, they have a great deal of control on the official per capita GDP data in order to obtain estimates lower than the true ones), one would certainly expect regions on one side of the cut-off to be systematically different from those on the other side. However, Lee (2008) shows that if individuals do not have precise control over the forcing variable, variation in treatment status will be randomized in a neighbourhood of the cut-off. In this case the RDD can be considered is “as good as” a local randomly assignment. In our case, the selection process leads to a high degree of uncertainty over the assignment results. The cut-off point is fixed as the 75% of the average per capita GDP in the UE-15, that is known only after the availability of the data referring to all regions. Moreover, Eurostat has a strict control over the procedure estimating the regional accounts.

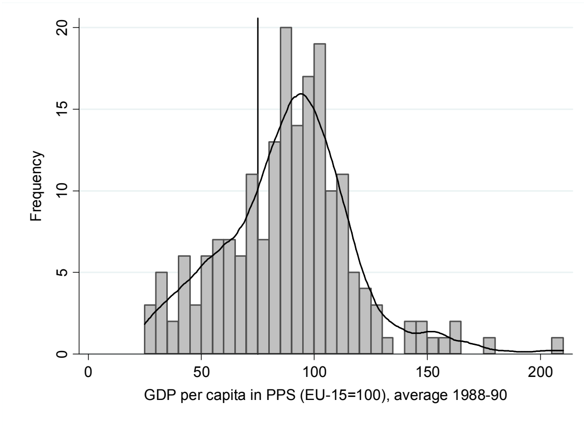
The evidence of a jump in the conditional density of the forcing variable can be a test of the imprecision of control over the forcing variable, as suggested in McCrary (2008): if there is some degree of sorting of the regions around the threshold, the appropriateness of the RDD in this contest is dubious. In Figure 6.1 we present histograms of the distribution of the GDP in PPS, average 1988-1990, using different bin sizes. Reducing the bin size, a moderate evidence of some differences around the cut-off point appears. However, a deeper analysis indicates that the level of per capita GDP went under the threshold only in two treated regions in the period considered (1988-1990), that is Northern Ireland and Flevoland. The same evidence arose also in Merseyside, but in this case the level of per capita GDP remained under the threshold also in the following years. A more formal test of manipulation related to continuity of the forcing variable density function is presented in McCrary (2008). We present here in Figure 7.2 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. 7.1 – GDP per capita distribution in PPS, average 1988-1990

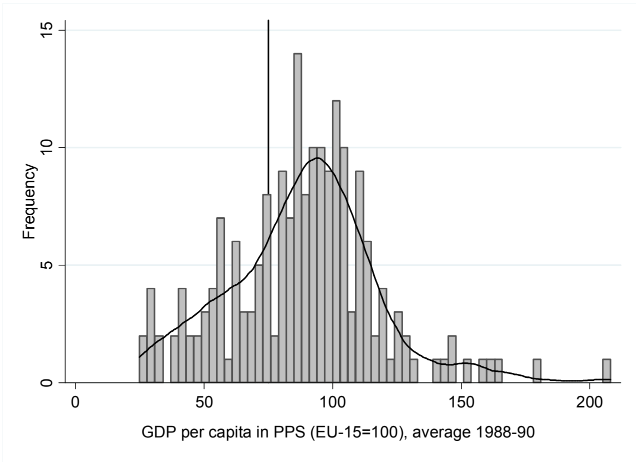
a) binsize=10



b) binsize=5

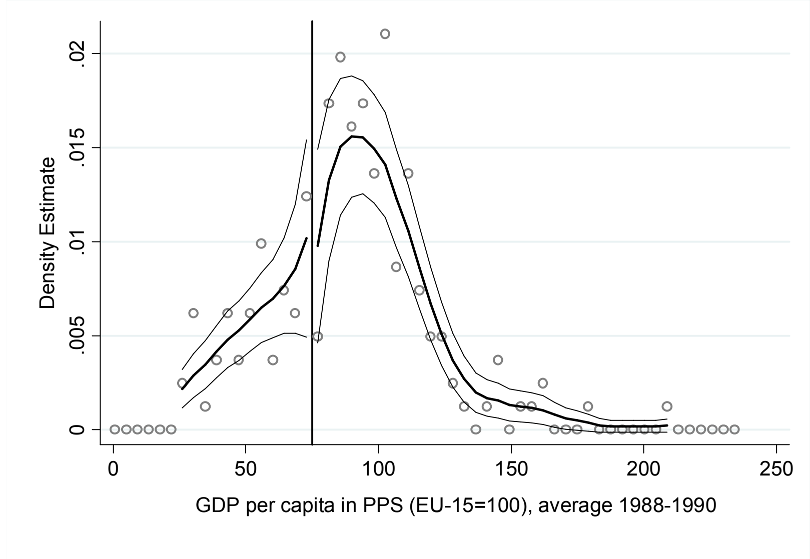


c) binsize=3



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.

Fig. 7.2 - Estimated density of the forcing variable at the cut-off (per capita GDP, average 1988-1990)



We tested the effects using different kernels and bandwidth. In Table 7.1 the results obtained by a bandwidth equal to 30 are presented. Some discontinuities are captured only around the values from 75 to 80, however close to the hypothesized cut-off.

Tab. 7.1 - Test of different cut-off points of the forcing variables

cut-off point	Epanechnikov kernel	Gaussian kernel
50	0.196	0.109
	(-0.557)	(0.560)
55	-0.197	-0.250
	(-0.520)	(0.517)
60	-0.376	-0.353
	(0.369)	(0.403)
65	-0.550	-0.462
	(-0.355)	(0.336)
70	-0.404	-0.296
	(-0.389)	(0.340)
75	-0.638	-0.628
	(0.387) (**)	(0.306) (**)
80	-0.577	-0.6407041
	(0.296) (*)	(0.294) (**)
85	-0.293	-0.378
	(0.261)	(-0.239)
90	0.202	0.152
	(0.244)	(0.204)
95	0.470	0.413
	(0.216) (*)	(0.243) (*)
100	0.306	0.274
	(0.244)	(0.228)

Note: Bootstrapped standard errors in parentheses. Bandwidth =30, 100 replication; (*), (**), (***) = significant at 10%, 5%, 1% respectively.

An important test regarding the assumptions underlying the RDD is to verify that there are no jumps at the cut-off point in variables that should not be affected by the treatment. The absence of discontinuities around the threshold supports the causality relation between the jump in the outcome variable and the treatment. We look at possible jumps in the value of some demographic and related to the labour market covariates at the cut-off point using the non parametric local linear regression and three different kernel (Gaussian, Epanechnikov, rectangular). Some of the results are presented in Table 7.2.

Tab. 7.2 - Non-parametric estimates using other covariates (one-side local linear regressions at the cut-off)

Covariates	Epanechnikov kernel	Gaussian kernel	Rectangle kernel
Population (1990)	486 (342)	475 (362)	575 (508)
Population density (1990)	.055 (.207)	.048 (.170)	-.020 (.241)
Employment (1995)	124 (198)	113 (213)	129 (227)
Employment rate (1995)	.026 (.030)	.024 (.025)	.0133 (.039)
Share of agricultural employment (1995)	.059 (019) (***)	.058 (.016) (***)	.046 (.018) (***)
Share of population over 65 years (1990)	.084 (.011) (***)	.084 (.011) (***)	.073 (.016) (***)

Note: Bootstrapped standard errors in parentheses. Bandwidth=30. (*), (**), (***) = significant at 10%, 5%, 1% respectively.

Overall we do not detect a statistically significant jump. Exception are the share of agricultural employment and the share of population over 65 years. However, even it is difficult to rationalize such discontinuities, a parametric estimation of the treatment effect including this variable in the model gives basically the same results we presented before.

Tab. 7.3 - Parametric estimates using different polynomial fit. Dependent variable: Per capita GDP average annual growth rate period 1995-2006.
Spatial model estimates. X=GDPpc in PPS (EU-15=100, average 1988-1990)

	Eq. 1 (lin. reg.)	Eq. 2 (spat. error)	Eq. 3 (spat. lag)	Eq. 4 (spat. error)	Eq. 5 (spat. error)	Eq. 6 (spat. error)	Eq. 7 (spat. error)	Eq. 8 (spat. error)	Eq. 9 (spat. error)	Eq. 10 (spat. error)
	dependent var.: GDP growth rate									
Constant	1.361	1.367	0.347	1.595	1.169	3.131	3.434	3.575	6.829	6.765
	(3.40)**	(3.75)**	(0.95)	(9.80)**	(3.10)**	(4.27)**	(2.92)**	(3.02)**	(1.52)	(1.50)
X	0.002	0.002	0.002		0.004	-0.029	-0.034	-0.037	-0.118	-0.117
	(0.52)	(0.62)	(0.63)		(1.15)	(2.43)*	(1.79)	(1.91)	(1.09)	(1.07)
X^2						0.000	0.000	0.000	0.001	0.001
						(2.87)**	(2.17)*	(2.29)*	(0.96)	(0.95)
X^3									-0.000	-0.000
									(0.79)	(0.78)
Treatment Dummy	1.094	0.975	0.611	0.872	2.055	0.499	0.138	-1.202	-4.275	-2.378
	(4.22)**	(3.57)**	(3.17)**	(3.84)**	(2.67)**	(1.66)	(0.11)	(0.61)	(0.95)	(0.39)
Treat. Dum.* X					-0.018		0.005	0.057	0.126	0.004
					(1.50)		(0.27)	(0.80)	(1.10)	(0.01)
Treat. Dum.* X^2								0.000	-0.001	0.002
								(0.68)	(1.01)	(0.28)
Treat. Dum.* X^3										0.000
										(0.43)
λ (spat. error) or ρ (spat. lag)	-	0.6299	0.6193	0.6298	0.6653	0.6632	0.6582	0.6548	0.6579	0.6591
λ or ρ z-statistic	-	(7.67)**	(7.56)**	(7.61)**	(8.10)**	(8.45)**	(7.68)**	(7.65)**	(7.73)**	(7.82)**
Obs	177	177	177	177	177	177	177	177	177	177
ll(null)	-250.6	-232.1	-232.1	-232.3	-231.6	-231.7	-227.7	-227.2	-227.2	-226.8
ll(model)	-232.1	-203.5	-203.2	-203.8	-201.9	-200.0	-200.0	-199.6	-199.2	-199.2
df	3	5	5	4	6	6	7	8	9	10
AIC	470.2	417.0	416.4	415.6	415.8	412.1	413.9	415.2	416.5	418.4
BIC	479.7	432.9	432.3	428.3	434.9	431.1	436.2	440.6	445.1	450.1

In parentheses: 1) robust standard errors for regression coefficients; 2) z-statistic for λ or ρ coefficients.
* significant at 5% level; ** significant at 1% level.

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 (Table 7.3) and by a spatial lag model (Table 7.4). Even if the selected specification (using the AIC and BIC criteria) is different between the two models, the estimates confirm our previous results.

Tab. 7.4 - Parametric estimates using different polynomial fit. Dependent variable: Per capita GDP average annual growth rate period 1995-2006.
Spatial model estimates. Restricted sample. X=GDPpc in PPS (EU-15=100, average 1988-1990)

	Eq. 1 (lin. reg.)	Eq. 2 (spat. lag)	Eq. 3 (spat. lag)	Eq. 4 (spat. lag)	Eq. 5 (spat. lag)	Eq. 6 (spat. lag)	Eq. 7 (spat. lag)	Eq. 8 (spat. lag)	Eq. 9 (spat. lag)
	dependent var.: GDP growth rate								
Constant	2.209	0.684	0.507	0.451	2.895	13.06	12.413	97.255	125.841
	(2.48)*	(0.92)	(3.70)**	(0.58)	(1.11)	(1.66)	(1.47)	(1.18)	(1.50)
X	-0.006	-0.002		0.001	-0.054	-0.271	-0.257	-3.004	-3.929
	(0.63)	(0.25)		(0.07)	(0.94)	(1.61)	(1.42)	(1.13)	(1.45)
X^2					0.000	0.001	0.001	0.031	0.041
					(0.95)	(1.62)	(1.43)	(1.09)	(1.40)
X^3								-0.000	-0.000
								(1.04)	(1.35)
Treatment Dummy	0.872	0.338	0.395	1.106	0.179	-5.807	-3.353	-63.163	-182.898
	(2.36)*	(1.44)	(2.72)**	(0.78)	(0.60)	(1.31)	(0.26)	(1.08)	(1.59)
Treat. Dum.* X				-0.011		0.077	0.005	1.530	6.908
				(0.55)		(1.36)	(0.01)	(1.02)	(1.48)
Treat. Dum.* X^2							0.001	-0.009	-0.091
							(0.20)	(0.95)	(1.36)
Treat. Dum.* X^3									0.000
									(1.26)
ρ (spat. lag)	-	0.6776	0.6786	0.6798	0.6805	0.6764	0.6749	0.6739	0.6705
ρ robust std err.	-	(9.04)**	(9.22)**	(9.06)**	(9.09)**	(9.19)**	(9.50)**	(9.45)**	(9.60)**
Obs	133	133	133	133	133	133	133	133	133
ll(null)	-188.6	-172.7	-173.0	-172.7	-172.4	-171.0	-170.5	-169.8	-168.7
ll(model)	-172.7	-141.3	-141.3	-141.0	-140.5	-139.3	-139.3	-138.6	-137.7
df	3	5	4	6	6	7	8	9	10
AIC	351.4	292.5	290.6	294.0	293.0	292.7	294.6	295.2	295.4
BIC	360.1	307.0	302.2	311.4	310.4	312.9	317.7	321.2	324.3

In parentheses: 1) robust standard errors for regression coefficients; 2) z-statistic for ρ coefficients.
* significant at 5% level; ** significant at 1% level.

7. Conclusions

In this paper we analyse the effects of the European Regional policy using a counterfactual methodological approach based on the RDD. Although a large amount of literature has been devoted to the econometric evaluation of the impact of such a type of policy, the empirical evidence is still mixed and ambiguous. While some authors find evidence of a significant positive impact of Structural Funds on regional growth and convergence, others only find a weak impact, or none at all. The main reasons at the root of this are the low availability and comparability of regional expenditure and income data, but also the technical and methodological problems faced when trying to identify the causal relation between Regional policy actually implemented and the observed outcome.

Recently the literature about policy evaluation has grown, proposing an innovative approach in the field of causal inference with observational data, when the policy (the "treatment") cannot be randomly assigned. Rather curiously, very few studies tried to apply the new techniques to the evaluation of the impact of UE Regional policy on regional growth. Our analysis intends to assess the effectiveness of UE Regional policy using a counterfactual method, comparing the economic scenario arising under policy interventions with a 'counterfactual' situation - what would have happened if the policies were not implemented. This approach, based on the notion of "potential outcomes", at the basis of the Rubin causal model, is now the most widely used theoretical framework for causal inference (Holland, 1986). To this end we properly built the appropriate economic and financial regional data - a great effort has been done in order to estimate the Structural Found expenditure by regions- and we widely test the plausibility of a RDD approach in estimation or the EU Regional Policy effects.

Indeed, the basic idea of the paper is to exploit the allocation rule of regional UE transfer: regions with a per capita GDP level below 75% of the EU average receive a huge amount of UE Structural Funds transfers. This rule gives rise to a RDD, based to the jump in the probability of EU transfer receipt at the 75% cut-off point.

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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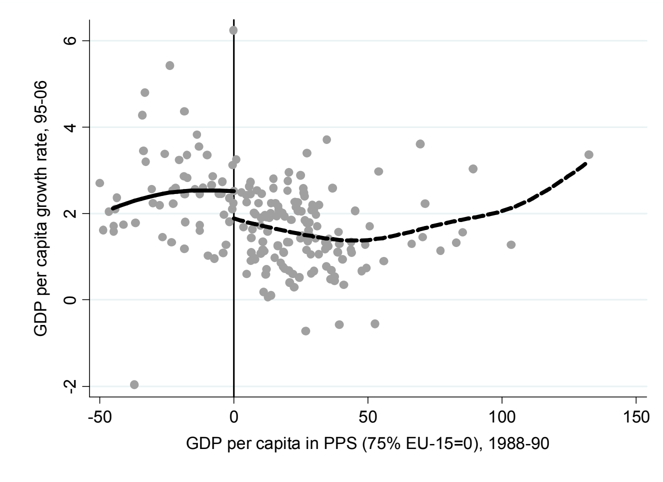
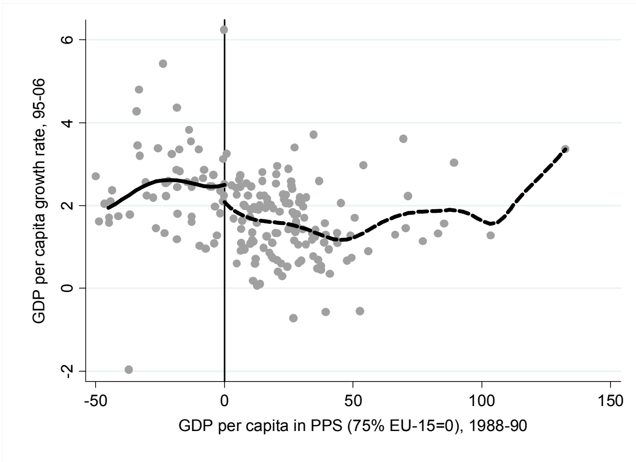
Appendix

A.1 – Further robustness proofs

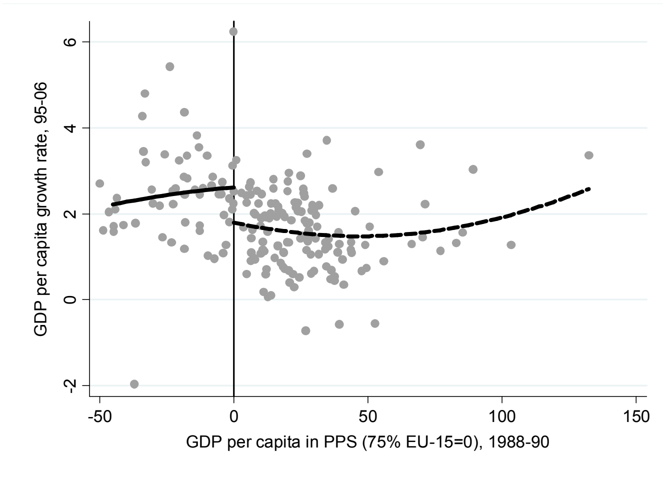
a) Optimal bandwidth (21.3)



b) Half of optimal bandwidth



c) Double of optimal bandwidth



A.2 – Parametric estimates using different polynomial fit. Dependent variable: Per capita GDP average annual growth rate period 1995-2006. X=log of GDPpc in PPS (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	-0.576	1.571	2.584	-18.925	90.255	403.611	1,133.00	908.554
	(0.18)	(21.18)**	(0.54)	(0.64)	(0.77)	(3.42)**	(0.26)	(0.24)
X	0.225		-0.106	4.231	-18.27	-83.194	-308.762	-239.123
	(0.66)		(0.21)	(0.65)	(0.75)	(3.41)**	(0.23)	(0.21)
X^2				-0.218	0.94	4.302	27.544	20.345
				(0.61)	(0.74)	(3.41)**	(0.2)	(0.17)
X^3							-0.798	-0.55
							(0.17)	(0.13)
Treatment Dummy	1.048	0.902	-4.617	1.047	-20.009	-524.811	-719.86	0
	(3.92)**	(5.14)**	(0.72)	(3.87)**	(0.87)	(2.96)**	(0.61)	(.)
Treat. Dummy* X			0.612		2.276	110.904	153.087	-86.704
			(0.89)		(0.91)	(2.84)**	(0.6)	(0.68)
Treat. Dum.* X^2						-5.852	-8.133	18.528
						(2.71)**	(0.59)	(0.67)
Treat. Dum.* X^3								-0.989
								(0.66)
Observations	190	190	190	190	190	190	190	190
R-squared	0.16	0.15	0.16	0.16	0.16	0.19	0.2	0.22
RMSE	0.973	0.972	0.973	0.975	0.974	0.957	0.960	0.959
AIC	531.9	530.4	532.9	533.4	534.1	528.6	524.5	530.3
BIC	541.6	536.9	545.9	546.4	550.4	548.0	537.5	553.1

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

A.3 – Parametric estimates using different polynomial fit: restricted sample. Dependent variable: Per capita GDP average annual growth rate period 1995-2005. X=log of GDPpc in PPS (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	5.517	1.648	6.391	15.165	208.284	916.299	-25,383.88	504.713
	-0.8	(20.29)**	(0.76)	(0.12)	(0.55)	(1.02)	(1.49)	(1.69)
X	-0.409		-0.501	-2.5	-43.219	-192.868	8,200.62	0
	(0.56)		(0.56)	(0.09)	(0.53)	(1.01)	(1.51)	(.)
X^2				0.113	2.259	10.166	-882.641	-16.808
				(0.08)	(0.53)	(1.01)	(1.53)	(1.68)
X^3							31.652	1.182
							(1.55)	(1.68)
Treatment Dummy	0.728	0.899	0.506	0.729	-1.867	-24.793	38.133	-154.454
	(1.96)	(4.96)**	(0.28)	(1.96)	(0.35)	(0.87)	(0.7)	(2.45)*
Treat. Dummy* X			0.003		0.035	0.63	-1.165	6.89
			(0.12)		(0.47)	(0.84)	(0.76)	(2.33)*
Treat. Dum.* X^2						-0.004	0.009	-0.105
						(0.78)	(0.82)	(2.17)*
Treat. Dum.* X^3								0.001
								(2.04)*
Observations	142	142	142	142	142	142	142	142
R-squared	0.18	0.18	0.18	0.18	0.18	0.19	0.21	0.22
RMSE	0.895	0.893	0.898	0.898	0.900	0.901	0.894	0.885
AIC	374.4	372.8	376.4	376.4	378.0	377.2	376.0	375.0
BIC	383.3	378.7	388.2	388.2	392.8	392.0	393.7	395.7

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