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**SPATIAL DISCONTINUITY FOR THE IMPACT ASSESSMENT OF
THE EU REGIONAL POLICY.
THE CASE OF ITALIAN OBJECTIVE 1 REGIONS.**

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Spatial discontinuity for the impact assessment of the EU Regional Policy.

The case of Italian Objective 1 regions

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Abstract

The capacity of the Regional Policy of the European Union (EU) to reduce the gap between the core and the periphery of the Union is still controversial. This paper revisits the question by exploiting treatment effect methods with a spatial approach never previously applied to the analysis of this policy. The spatial discontinuity represented by the administrative boundaries between ‘Objective 1’ and ‘non-Objective 1’ regions makes it possible to estimate the causal impact of the EU Regional Policy on Italian ‘Objective 1’ regions where the EU has addressed a large amount of resources over the past decades. By focusing on the sub-sample of municipalities contiguous to the ‘policy-change boundary’ and by matching them according to the segment of the boundary of which they belong, the ‘Spatial RDD’ model shows that the EU Regional Policy produced a positive impact on employment levels. The positive impact is concentrated in a specific set of economic sectors directly relevant to the policy action. In addition, there is no evidence of any displacement of resources away from other non-treated regions.

Keywords: Regional Policy of the European Union, treatment effect methods, policy evaluation, regions, European Union, RDD.

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Introduction

The Regional Policy is the main tool adopted by the European Union (EU) in order to support territorial cohesion. The EU Regional Policy is financially supported by the Structural Funds (SF) and absorbs roughly 40% of the Total EU Budget. The largest part of its resources is addressed to the most disadvantaged areas of the Union (i.e. the regions with a GDP per capita below 75% of the EU average): the ‘Objective 1’ (until 2006) or ‘Convergence’ regions (2007-2013 programming period), in order to make them capable of benefiting from the European integration process (Armstrong and Taylor, 2000). The main intended outcomes of the Policy in these areas is increasing employment and GDP and favoring sustainable local development. Several different measures are financed for this purpose: the European Regional Development Fund (ERDF) funds major infrastructural projects but also incentives for firms’ productivity, research and development activities and support for public services. Individual projects aiming at sustaining education and employment are instead largely financed by the European Social Fund (ESF). Finally, Rural Development is financially supported by the Second Pillar of the Common Agricultural Policy (CAP) within the SF scheme or through a separated funding stream (2007-2013 programming period).

The capacity of the EU Regional Policy to support these disadvantaged areas in converging to the wealthiest European regions, however, is still under discussion both among scholars and policy makers. The difficulties in isolating the policy effects from other contextual conditions that characterize the beneficiary regions is a major challenge for any empirical analysis and might have made it impossible to reach a consensus on the policy impact.

The endogeneity caused by these interdependencies is a major challenge for any impact evaluation analysis and especially for those one carried out within a ‘classical regression framework’, that represent the large majority of the EU Regional Policy literature. Up to now, in fact, only a few studies have applied treatment effect methods, that instead can more easily deal with the endogeneity issue¹ by taking advantage of the randomized experiments properties re-creating a ‘as good as random’ scenario in which ‘treatment’ could be thought to be randomly assigned (Blundell and Costa Dias, 2009).

The original contribution of this paper goes precisely in this direction. In particular, it applies a Regression Discontinuity Design (RDD) that innovatively exploits the spatial discontinuity of the administrative boundaries between ‘Objective 1’ and ‘non-Objective 1’ regions. Spatial units (municipalities) closer and closer to the ‘policy-change boundary” will represent the ‘as good as random’ scenario in which not treated observations are a good counterfactual for the treated.

The paper looks in particular at to what extent the EU Regional Policy has been able to support employment in the ‘Objective 1’ Italian regions by looking at employment levels in their municipalities. The empirical analysis shows that the EU Regional Policy produced a positive impact on employment. The positive impact

¹ Treatment effect methods have been shown extremely powerful in policy evaluation as they eliminate, by comparing two randomly defined groups of observations, any sources of bias succeeding in ultimately capturing the exogenous effect of the treatment.

is concentrated in the economic sectors mostly linked with a territorial development process (construction manufacturing and tourism) and so that directly relevant to the Regional policy aim. In addition, the job creation fostered by the Policy was not at the expense of the richer ‘Northern Italy’ since there is no evidence of any displacement of resources away from other non-treated regions. Hence, the original ‘Spatial RDD’ analysis proposed removes endogeneity from the estimation of the EU Regional Policy impact and concludes, in contrast to most of the ‘classical regression framework’ analyses, that the Policy has indeed supported employment in the most disadvantaged regions and persistently underdeveloped areas of the Union.

The paper is structured as follows: Section two discusses the relevant literature in order to shed light on the existing gap in the EU Regional Policy literature in so far as treatment effect methods are concerned. Section three tests the pre-conditions that need to be in place in order to exploiting administrative boundaries as a discontinuity and to estimate the EU Regional Policy impact in the Italian ‘Objective 1’ regions. Section four presents the RDD models and dataset. Section five discusses the empirical results. Section six tests their external validity. Section seven performs the robustness checks and section eight concludes.

1. RDD in Policy evaluation: method and existing empirical applications

The true impact of the EU Regional Policy remains an unsolved puzzle. A number of papers within the ‘classical regression framework’ have suggested that it is inexistent (Boldrin and Canova, 2001; de Freitas et al., 2003; Dall’Erba et al., 2007; García-Milá and McGuire, 2001), mixed (Puigcerver-Peñalver, 2007) or dependent on policy structure and territorial conditioning factors (Ederveen, Gorter Mooij and Nahuis, 2002; Cappelen et al., 2003; Mohl and Hagen, 2010; Rodríguez-Pose and Fratesi, 2004). A variety of different methods have been used to address the challenge of identification: instrumental variables (Dall’Erba and Le Gallo, 2008; Ramajo, Márquez, Hewings and Salinas, 2008), panel data (Rodríguez-Pose and Fratesi, 2004; Soukiazis and Antunes, 2006) and an integrated use of them (Beugelsdijk and Effinger, 2005; Bouayad-agma, Vedrine and Turpin, 2010; Bouvet, 2005; Ederveen, De Groot and Nahuis, 2006; Esposti and Bussoletti, 2008; Mohl and Hagen, 2010).

However, only a few papers have taken advantage of experimental methods to evaluate the effect of the EU Regional Policy. In general, all analyses based on Regression Discontinuity Design (RDD) techniques identified their ‘as good as random’ scenario by exploiting the GDP criteria (75% of the European average GDP in purchasing power parity for regions to be eligible for large part of the EU Funds) that sharply discriminates the Policy assignment. By considering regions closer and closer to the assignment threshold value as randomly assigned to the treated or to the not-treated group, these analyses succeed in defining the policy counterfactual and consequently identifying the exogenous policy effect, showing how ‘Objective 1’ regions have been able to grow more than other regions (Becker, Egger, von Ehrlich and Fenge, 2010; Pellegrini et al., 2013). Moreover, they showed that the policy effect is influenced by the degree of the

regional absorptive capacity, measured by the quality of regional institutions and by the stock of human capital (Becker et al., 2013), and, for the Italian case, it is smaller the higher is the relative size of the service sector (Percoco, 2012). Finally, the EU Regional Policy impact appears greater if captured by parametric estimations rather than by non-parametric estimation techniques (Pellegrini et al., 2013).

None of these studies adopted a spatial version of the RDD, leveraging the spatial discontinuity at the boundaries between treated ('Objective 1') and not-treated ('non-Objective 1') spatial units. Applications of 'Spatial RDD' are however increasingly common in the evaluation of policies with a spatially defined distribution. The discontinuity represented by the administrative boundaries of US States has been used to evaluate the effect of being a 'Pro-Business State' (policy status derived by adopting a set of measures in favour of enterprises) on the States' productive structure (Holmes, 1998). Some other contributions have used the same approach to capture the impact of territorial policies implemented in Peru (Dell, 2010), United Kingdom (Einio and Overman, 2012; Gibbons et al., 2009), Spain (Jofre-Monseny, 2014) and in the United States (Freedman, 2013). For the Italian case spatial RDD has been employed to investigate the role of judicial efficiency in terms of firms' size (Menon and Giacomelli, 2012) and to study the effect of local minimum wages on economic development (de Blasio and Poy, 2014). To the best of our knowledge there are no analysis making use of this approach in order to identify the impact of the EU Regional Policy even if a 'Spatial RDD' approach has the potential to provide robust results in evaluating the impact of policies whose resources are distributed across space according to its economic characterization (Freedman, 2013; Holmes, 1998).

2. Spatial RDD for the impact assessment of the EU Regional Policy in Italian Objective 1 regions

This paper estimates the exogenous impact of the EU Regional Policy in a treatment effect framework based on a 'Spatial RDD', which identifies the policy counterfactual by taking advantage of spatial discontinuities. In line with the existing literature on 'Spatial RDD', this design should be focused on areas whose boundaries are associated with a change in policy status (Black, 1999; Holmes, 1998; Menon and Giacomelli, 2012), i.e. on Italian regions that share boundaries that imply a passage from an 'Objective 1' region to a 'non-Objective 1'. The Italian administrative regional subdivision is such that a maximum of five (NUTS2) regions can be included in the design (see Figures A.1 and A.2 in Appendix A): Marche, Lazio, Abruzzo, Molise and Campania. The threshold to which the discontinuity is related is therefore represented by the four segments of the 'policy-change boundary' among these five regions (Marche and Lazio are 'non-Objective 1' regions, and they are contiguous to the 'Objective 1' Abruzzo, Molise and Campania). Thus, the whole analysis sample comprises 1613 observations (the municipalities belonging to the five regions). The 99 contiguous municipalities (with black borders in Map A.1) on the two sides of each of the 'policy-change boundary' segments (b_1 , Marche-Abruzzo; b_2 , Abruzzo-Lazio; b_3 , Lazio-Molise and b_4 , Lazio-Campania) instead represent the 'as good as random' sub-sample in which 'randomized experiments' properties hold.

For all the observable variables that we can account for (under the constraint of data availability at the municipal level for Italy), the difference between their means in the ‘Objective 1’ and in the ‘non-Objective 1’ regions is smaller when computed for the 99 municipalities of the sub-sample (Table 1) as opposed to the whole-sample. In almost all cases the difference is found to be insignificant. Thus, with respect to observable factors, the 99 municipalities contiguous to the boundary are more similar to each other than all municipalities. Within this sub-sample observable characteristics are equally distributed across treated and untreated municipalities.

Table 1 here

Table 2 confirms that observations (municipalities) can be thought as randomly belonging to one (treated) or the other (control) side of the boundary by showing that there is no relation between the policy status (sharply changing at the boundary) and other observables (smoothly distributed across space).

Table 2 here

Thus, in this sub-sample treatment assignment depends in a discontinuous way (i.e. sharply) only on its conditioning factor (*distance* from the boundary) whereas all the other observable characteristics change smoothly across observations in space. As a consequence, within the sub-sample, observations that don’t get the treatment represent the counterfactual for those treated, as they are similar in everything (smooth distribution of all characteristics) except for the treatment (discontinuous jump). By assuming that unobservable characteristics are distributed similarly to the observables (Black, 1999), any discontinuity in the outcome variables (y) could be hence ascribed to the treatment (‘Objective 1’ Status).

The pre-conditions required by the analysis are met when focusing on the policy programming periods 1988-1993 and 1994-1999: the division of the regions into ‘Objective 1’ and ‘non-Objective 1’ over these periods maximizes the number of segments of the ‘policy-change boundary’ and hence the number of observations for the analysis. From the policy programming period 2000-2006 the number of boundaries implying a change in the policy status would be smaller given that Abruzzo lost its ‘Objective 1’ Status and, as a consequence, the focus of the analysis would have been further restricted from Marche, Lazio, Abruzzo, Molise and Campania to Lazio, Campania and Molise leading the set of ‘policy-change boundary’ to be composed by only two segments (Lazio-Campania and Lazio-Molise). In addition, during the policy programming periods 1988-1993 and 1994-1999, the policy of interest was the only one operating in the areas being studied. Since Italian unification, Southern Italy regions have always been targets for some form of developmental support, and this would have represented a problem in terms of isolating the effect of the EU Regional Policy from the influence of other policies operating in the same areas. However, during the 1990s the policy scheme used for them underwent redesign - in line with the generalised evolution of

development policies – with the adoption of a bottom-up perspective (New Regional Policy, OECD 2009). In 1992, the ‘extraordinary measures’ funded by the national government (whose overall impact is considered inexistent by a number of empirical studies) were abandoned and only from 1999 did a new policy scheme start to emerge (Cannari, Magnani and Pellegrini, 2009).

In addition, the choice of focusing on earlier policy programming periods of Structural Funds (1988-1993 and 1994-1999) instead of considering most recent ones guarantees a sufficiently long time period within which testing the estimation of the entire policy impact cleaning out from the pre-treatment differentiations between control and treated group (Andini and de Blasio, 2014; Pellegrini et al., 2013). By considering the policy over the period 1988-1999 the impact could be estimated with respect to a ten year variation of the outcome variable (variation 1991-2001) and also tested with respect to a correspondent variation over a longer time-window from 1991 to 2011. Even though the latter cannot represent the main variable of interest due to the large number of confounding factors that such a long period would involve, it is necessary to test for the results obtained by looking at the shorter outcome variation (see Section 7.2).

Finally, an analysis focused on Italy can also provide relevant insights for other European countries. The persistent ‘dualism’, which has long characterised the economies of Northern and Southern Italian regions reflects the disparities characterizing Europe’s richest and poorest regions, and on whose basis regions receive or are refused ‘Objective 1’ status. Some Northern Italian regions are among the richest in the Union whereas all Southern Italian regions are among the poorest.

3. The Model

Within the methodological framework discussed above, a basic version of equation (1) relates the dependent variable ‘employment variation between 1991 and 2001’ (Δy_{it}) to a dummy variable (*Policy*) that takes value=1 for the municipalities belonging to ‘Objective 1’ regions within the period 1988-1993 and 1994-1999.²

$$\Delta y_{it} = \beta_0 + \beta_1 Policy_{it-1} + \beta_2 IC_{it-1} + \beta_3 X_{it-1} + b_1 + b_2 + b_3 + b_4 + \varepsilon_{it} \quad (1)$$

Where IC_{it-1} accounts for the Initial Conditions (number of workers and of local plants), X_{it-1} accounts for municipalities’ observable characteristics, i stands for the observation (municipality) and t for time.³

In a standard OLS setting (our benchmark here) the model is estimated for the totality of the observations (1613) and without accounting for the policy discontinuity. In a RDD framework instead, the model is estimated for the 99 municipalities of the ‘as good as random’ sub-sample and it includes a set of four dummies (b_1, b_2, b_3 and b_4) each of them matching within each other the municipalities that share the same segment of the ‘policy-change boundary’ from either the treated and the non-treated sides of the boundary

² For the sake of clarity, in the Tables the variable *Policy* is mentioned as ‘Objective 1’ status.

³ $t=2001$; $t-1=1988-1999$ for the *Policy* variable and 1991 for all the other variables.

itself (Black, 1999; Holmes, 1998; Freedman, 2013; Jofre-Monseny, 2014; Menon and Giacomelli, 2012).⁴ The main strength of this kind of matching ('border strategy') is its capacity to eliminate the influence on policy impact of any contextual conditions. The matching provided by this whole set of dummies does not coincide with that provided by regional dummies. In the case of regional dummies, municipalities are grouped by region while with the 'policy-change boundary' dummies they are grouped by the boundary segment to which they belong (Black, 1999; Holmes, 1998). Only in this latter case, does the matching capture the similarities in the characterisation in terms of observables and non-observables. It defines a counterfactual that completely eliminates any omitted variable bias. Consequently, any discontinuity found in the outcome variables could only be ascribed to the discontinuity that discriminates between the treated and untreated groups in the sub-sample, namely the boundary (conditioning factor of the policy treatment).

The Policy effect investigated by model (1) is estimated here also in a general RDD setting. Instead of focusing on contiguous municipalities and matching them with the set of 'policy-change boundary' dummies ('border strategy', customary in 'Spatial RDD' applications⁵), Model (2) accounts for the discontinuity by including the *distance* of municipalities from the boundary, namely the 'forcing variable' of the treatment, following what is done by all 'general' RDD analyses irrespectively of the nature of the discontinuity that they exploit (Dell, 2010; Lee and Lemieux, 2010).⁶

$$\Delta y_{it} = \beta_0 + \beta_1 Policy_{it-1} + \beta_2 IC_{it-1} + \beta_3 X_{it-1} + Policy_{it-1} \sum_{p=1}^2 \gamma distance_i + \varepsilon_{it} \quad (2)$$

Where the notation is the same as in Equation (1) and *distance* is the Euclidean distance between the centroid of each municipality and the nearest point of the 'policy-change boundary'.

In both models (1) and (2), the variation of the number of municipal workers (Δy_{it}) is the key outcome variable since employment and GDP growth are the main intended outcome of the EU Regional Policy and since there is no availability of data on GDP at municipality level in Italy. In addition, considering workplace employment (the variation is computed for the number of workers in the plants located in the municipalities)

⁴In particular: b_1 is a dummy variable=1 for the municipalities on the segment of the 'policy-change boundary' between Marche and Abruzzo and =0 for all the others municipalities; b_2 is a dummy variable=1 for the municipalities on the segment of the 'policy-change boundary' between Lazio and Abruzzo and =0 for all the others municipalities; b_3 is a dummy variable=1 for the municipalities on the segment of the 'policy-change boundary' between Lazio and Molise and =0 for all the others municipalities; b_4 is a dummy variable=1 for the municipalities on the segment of the 'policy-change boundary' between Lazio and Campania and =0 for all the others municipalities.

⁵Black (1999); Holmes (1998); Jofre-Monseny (2014); Menon and Giacomelli (2012).

⁶ In principle, since model (2) is estimated for the whole-sample of the municipalities belonging to the five regions and not only for the 99 municipalities that are contiguous to the 'policy-change boundary', its results are more robust and precise. According to the literature to which we are referring on, however, model (1) is preferred for the main analysis taking the results of model (2), completely in line with the one estimated by model (1) as robustness check (see Table 5). This choice is driven also by an issue of lack of data related to the variable *distance* and involving 47 municipalities all located all in Marche region.

rather than the employment of resident people allows considering job creation as a proxy for the broader local development of the treated areas.

The *policy* variable is a dummy that takes value=1 for municipalities belonging to ‘Objective 1’ regions. This only captures the policy status of the municipalities and not the effective expenditure they benefit from. Using status eligibility instead of the actual intensity of the treatment of the EU Regional Policy, which operates through the voluntary participation of local actors applying for policy support by submitting projects to be financed, may mean running the risk of considering eligible observations treated when, in fact, no treatment was forthcoming. Unfortunately, local expenditure data, which would have allowed us to check that each municipality considered treated had received and spent funds, do not exist for the policy programming periods before 2000. In any case, coefficients estimated by considering the ‘Objective 1’ dummy capture the “Intention to treat effect” (ITT) that is the lower bound for the “Average treatment effect” (ATE) that a continuous policy variable would have captured (Battistin and Rettore, 2008). In addition, available data on Structural Funds expenditure for the period 2000-2006 show that each municipality in the sub-sample belonging to the ‘Objective 1’ regions in fact benefited from funds (Table 3), which makes it likely that this also applied in previous programming periods (1988-1999).

Table 3 here

In order to increase the efficiency of the estimates models (1) and (2) include also some additional regressors: the number of workers in local plants and the number of local plants at the beginning of the period accounts for the Initial Conditions (matrix IC_{it-1}) and the X_{it-1} matrix contains the control variables related to the municipalities’ socio-economic conditions: the degree of agglomeration (proxied by Population Density); the demographic structure of the population (proxied by the Dependency Ratio) and the level of human capital (proxied by the share of Uneducated Population). The inclusion of these additional variables should only increase the precision of the RDD results but since observables are smoothly distributed across treated and not-treated observations, their coefficients are not expected to be significant. The choice of these variables is strictly driven by the availability of data at such as disaggregated territorial level.

The main source of the data used in the model is the Italian National Statistical Office (ISTAT). In particular, data on employment come from the ‘Industry and Services Census’ datasets whereas control variables data come from the ‘Population and housing Census’ datasets. Additional data on regional transfers to municipalities (that will be used to check the robustness of the results) come instead from the Ministry of Interior.

4. Results

Table 4 summarises the results of the estimated model (1). The employment variation is initially related to the ‘Objective 1’ Status dummy and the ‘Initial conditions’⁷ (columns 1 and 3) and subsequently to a wider set of variables (columns 2 and 4).

The RDD model estimates positive and significant *policy* coefficients on the basis of its first specification (column 3) and the results do not change when the model includes control variables related to the socio-economic characteristics of the municipalities⁸ to increase the efficiency of the RDD estimation (column 4). These findings, obtained by eliminating all the endogeneity likely to affect the analysis, demonstrate that the Regional Policy’s impact is indeed positive for the economies of the Italian ‘Objective 1’ regions.

By succeeding in disentangling the policy from all such elements, assuming the latter to be equally distributed over the space, the analysis found that the policy had a positive causality effect. This result is not only exogenous and unbiased (thanks to the ‘randomized experiment’ properties exploited) but also contrary to the result that the analysis would have yielded if performed in a basic OLS setting (columns 1 and 2 in Table 4). An OLS analysis, by failing to deal with omitted variables and reverse causality issues that would affect the relation between policy and economic performance, is unable to estimate significant coefficients. Moreover, the estimated coefficients appear to have an opposite sign with respect to the exogenous ones provided by the RDD.

Table 4 here

As expected, furthermore, the result of the ‘border strategy’ analysis are totally confirmed by those estimated by model (2) in a general RDD specification using the *distance* as ‘forcing variable’ for the treatment (Table 5): the basic OLS regression is unable to estimate significant coefficients (when the *distance* does not enter the model - polynomial degree=0 - we have the same results as in Table 4). By entering the *distance* from the discontinuity in the RDD models (Polynomial degree=1 and 2 of Table 5) instead, we found that the EU Regional Policy plays a positive and significant role on employment. The coefficients are also of similar magnitude to those estimated by the main analysis.

Table 5 here

⁷ Specification of the model without Initial Conditions are not reported here in the interest of space but they lead to similar coefficients.

⁸ The variables account more specifically for the demographic structure (dependency ratio), the human capital endowment (share of non-educated population) and the degree of agglomeration (population density) of the municipalities.

5. External validity

RDD models estimate the policy's net impact at the cut-off of the distribution. In order to determine if the effect estimated is valid for the whole set of treated observations (i.e. external validity, which in our case refers to the rest of EU 'Objective 1' regions) we can test the results by reproducing the analysis in a context as more similar as possible to the one of the main study (Battistin and Rettore, 2008; Blundell and Costa-Dias, 2009). In the case of Italian 'Objective 1' regions, Spain seems to be the most suitable test.

During the period under analysis, EU Regional Policy in Spain and in Italy was implemented with a similar approach, both in terms of resources committed and territorial coverage. As concerns Spain, regions that share a 'policy-change boundary' are: Castilla la Mancha, Castilla-Leon, Cantabria and Comunidad Valenciana ('Objective 1') and Pais Basco, La Rioja, Aragon and Cataluna (non-'Objective 1'). The number of municipalities belonging to these regions totals 5893. The analysis is hence reproduced within this setting to see if the positive and significant impact of EU Regional Policy found for the Italian 'Objective 1' regions is confirmed in this analogous context. If it did, the main results, found at the discontinuity, could be fairly interpreted as being valid overall.

Because of the physical conformation of the Spanish municipalities, within a territory that is not all contiguous but rather distributed over many separated areas spread over a larger area, it was preferred to run the general RDD model including the forcing variable *distance* (Equation 2 in Section 4) rather than restricting the focus to the contiguous municipalities matched by the 'policy-change boundary' dummies (Equation 1 in Section 4).

In order to make the two cases comparable, the model was also re-estimated for the Italian case based on data available for Spanish municipalities (for which there is no information on initial conditions in terms of number of local plants)⁹ and the results are reported in Table 6.

Table 6 here

It emerges that for Spain too, the impact of the *policy* is positive, significant and of a similar extent with respect to Italy.

In addition, if Italian and Spanish municipalities are pooled together, the same model can be run for them all, allowing all the coefficients to vary by country (i.e. each variable interacting with a 'country' dummy that matches municipalities by country of origin):

$$Country * \Delta y_{it} = \beta_0 + \beta_1 Country * Policy_{it-1} + \beta_2 Country * IC_{it-1} + Country * Policy_{it-1} \sum_{p=1}^2 \gamma dist_i + \varepsilon_{it} \quad (3)$$

⁹In order to estimate the same model for Italy and Spain, Matrix IC_{it-1} of Equation (2) here contains only the number of workers and not the number of local plants for both the Italian and the Spanish observations.

The results are shown in Table 7, and confirm the findings already obtained by estimating the two RDD models separately.

Table 7 here

According to this classical way of checking for the external validity of the RDD strategy, the local average treatment effect estimated for the municipalities on the boundary could be interpreted as also valid for the entire sample.

6. Robustness checks

Apart from being internally and externally valid the results presented above are also robust to a series of potential issues typically critical for both standard and ‘Spatial’ RDD analyses.

6.1 Spillovers across boundary

Although the Regional Policy is by nature ‘spatially targeted’, its effects, whether positive or negative, are unlikely to be totally self-contained within the territory at which the policy measures were originally targeted (Bondonio and Greenbaum, 2003; Einio and Overman, 2012; Freedman, 2013; Glaeser and Gottlieb, 2009). The effect of the policy implemented in treated areas could in fact spread to the not-treated ones generating a ‘spatial sorting’ effect, which is particularly relevant when the size of the units of analysis is very small, as happens here (municipality). In order to benefit from the specific financial incentives or grants offered by a spatially targeted policy scheme, for instance, firms that would otherwise have chosen to locate in untreated areas can lead to locate in adjacent treated areas in order to obtain the policy support. In this case, the treatment effect estimated would be the result of the sum of the *policy* effect and this sorting effect (attracting new firms in the treated area at the expenses of untreated areas rather than creating new employment opportunities).

‘Spatial sorting’ has been largely studied in literature (Einio and Overman, 2012; Fehrenbacher and Pedell, 2012) and also as concerns Italy (Accetturo et al., 2014; Andini and de Blasio, 2014; Bronzini and de Blasio, 2006; de Castris and Pellegrini, 2005).

Here we check for ‘spatial sorting’ by performing the ‘Displacement Test’ (Einio and Overman, 2012). The assumption is that changing the location decision in order to benefit from the policy is easier the closer the treated municipalities are: ‘spatial sorting’ is expected to be larger for control municipalities closer to the boundary. Consequently, a treatment effect coefficient that includes ‘spatial sorting’ is higher the smaller the *distance* from the boundary of municipalities included as controls in the models. Thus, if by extending the control group to more distant control municipalities the estimated coefficients decrease, the impact found ‘at the discontinuity’ would probably be upwardly biased, including not only the direct *policy* effect but also the ‘spatial sorting’ from untreated municipalities.

In methodological terms, the ‘displacement test’ runs the RDD model by focusing initially on the control municipalities closest to the boundary and including afterwards the control municipalities belonging to bands increasingly far from the boundary. Each sample is hence made up of different rings/bands of control observations, matched within each other by their corresponding ring/band.

Here we perform the test by comparing treated observations within 15 km from the ‘policy-change boundary’ with five different samples of control municipalities, the first comprised by control municipalities within 15 km (1st band), the second by the control municipalities within 50 km (2nd band), the third control municipalities within 75 km (3rd band), the fourth control municipalities within 100 km (4th band) and the last comprising all untreated municipalities. Each version of the model, related to each of the control samples, includes therefore a set of dummies matching together the municipalities belonging to the same band.¹⁰

Table 8 here

The results of the different models estimated are reported in Table 8 and show that according to the RDD specifications (columns 2 and 3) the coefficients of interest are positive and significant irrespective of the sample of control municipalities used. Even if we only consider the full sample of control municipalities, for which ‘spatial sorting’ with respect to the treated observations is necessarily less likely,¹¹ the EU policy’s impact is still positive and significant. The coefficients’ magnitude does not increase in direct proportion to the municipalities’ proximity to the boundary, as the largest coefficient being, at least in column 2, that obtained by looking at the whole-sample of control municipalities.

According to this test, which is capable of disentangling the net *policy* effect from the ‘spatial sorting’, it seems that the effect of EU Regional Policy is positive by itself and not driven by any sorting effect. Hence, the policy does not cause the displacement of economic activities from the untreated to treated areas. This is a very relevant results. Firstly, with respect to the nature of the policy: pursuing territorial cohesion does not mean damaging the richest regions by shifting their economic activities to the poorest areas. Secondly, with respect to the scenario of interest: EU Regional Policy supports an autonomous development for the Italian Southern areas, without producing negative externalities for other regions.

6.2 Long run effect

The time window for the implementation of counterfactual analyses needs to be sufficiently long in order to check whether or not the treatment of interest has produced changes in the observable characteristics of the treated and control observations. Furthermore, it is important to ensure that the final differences are due to

¹⁰ The specification of the model adopted here is the one of Equation 2, which accounts for discontinuity by having recourse to the forcing variable *distance*. Since the focus here is not only on contiguous municipalities, this solution appears to be more appropriate than the specification of Equation 1(‘border strategy’).

¹¹ Their *distances* to the boundary are of up to 200 kms.

the treatment and that they do not simply reflect corresponding pre-treatment conditions. This is one of the reasons why the analysis looks at earlier policy programming periods: in this case, we can test for policy impact over a period of more than 10 years. In particular, the main analysis estimated the impact of the policy on variation in employment between 1991 and 2001¹² and this paragraph shows how the results obtained are valid also over a longer time period 1991-2011. Table 9 illustrates that even in relation to the employment variation 1991-2011 the ‘Objective 1’ dummy coefficient remains positive, significant and similar in extent to that estimated with respect to the 1991-2001 employment variation.

Table 9 here

It not only means that the impact estimated with a shorter lag between treatment and outcome (Table 4) is reliable but that it is also valid for the long term. EU Regional Policy as carried out until 1999 was capable of setting a real local development process in the most disadvantaged Italian areas.

6.3 Confounding factors

The assumption on which RDD relies is that in the ‘as good as random’ sample, treatment is the only discontinuity, whereas everything else is randomly distributed and changes smoothly. The different spatial patterns of the treatment with respect to other aspects makes it possible to separate their effects.

By contrast, if a phenomenon is distributed across space in the same way as the EU Regional Policy and correlated to this policy, its role would remain ‘hidden’ and included in the estimated policy impact as ‘confounding factor’. It might be the case for instance, if other assisting enterprises’ policies (observable factor) are active with the same spatial distributions of the policy of interest.

Here, the ‘policy-change boundary’ is not a regional boundary but is composed by different segments of boundaries. Moreover, most of the non-EU funded policies directly implemented by the Italian regions do not directly overlap with EU Regional Policy targets: Italian regions spending autonomy is concentrated in areas such as healthcare or social services. In addition, national-level development policies directly linked to EU Regional Policy targets (e.g., national policies targeted to the most underutilized areas, the current “Fondo per lo Sviluppo e la Coesione”) were not in operation during the period here investigated (see Section 3).

However, the following checks make sure that the discontinuity is correlated only to treatment and that impact estimation is not influenced by ‘confounding factors’ related to such regional effects. For most checks, the general idea was to re-estimate the analysis within a placebo ‘as good as random’ sample created

¹² The reason why the analysis prefers to use the shortest variation as principal reference is because the number and the importance of potential confounding factors (see Section 7.3) would be higher the longer the lag between the treatment assignment and the economic performance measure.

with respect to ‘mock’ discontinuities and with the expectation of not finding any significant policy impact in terms of employment variation.

In this framework, Table 10 shows the results obtained by looking at the true boundary, but in a period (1971-1981 and 1981-1991) when no discontinuity should be present as the policy had not been implemented.

Table 10 here

Table 11 shows results obtained by shifting the true boundary within the control group: the model here compares all untreated municipalities, assigning the mock treated status to the municipalities contiguous to the true boundary and taking the municipalities contiguous to them as controls.

Table 11 here

On the contrary, the model presented in Table 12 compares municipalities contiguous to the boundary between Molise and Campania, which do not represent a discontinuity as both regions are ‘Objective 1’. In this case, we are comparing municipalities that are all treated assigning a ‘mock’ control status to the Molise’ municipalities.

Table 12 here

These checks handle the issue of ‘confounding factors’ by illustrating how regional borders and ‘policy-change boundary’ discriminate observations between two different couples of treatment-control groups. As far as the aim of the analysis is to identify the effect of EU Regional Policy, only the ‘policy-change boundary’ provides a control group capable of being a counterfactual for the treated group, leading to an exogenous estimation of the treatment effect, disentangled from all other correlated aspects.

An additional piece of evidence confirms that the ‘policy-change boundary’ is only related to Regional Policy: if the EU Regional Policy dummy is substituted by a continuous variable accounting for the total amount of ‘transfers’ given from the regions to the municipalities (source of data: Ministry of Interior – see Section 4), the model still delivers insignificant policy coefficients. The meaning of the relation between this variable and the employment variation does not lend itself to easy interpretation: the ‘transfers’ variable is a large ‘container’ on which funding from very different kind of policies converge. The purpose of looking at this relation, however, is to check if at the discontinuity point other sources of local financial support behave in the same way as the EU Regional Policy. Results of this test are reported in Table 13.

Table 13 here

6.4 Sectorial impact and external shocks

The EU Regional Policy explicitly aims to support the development of specific sectors of strategic importance for local economic development processes. Consequently, we should expect that the coefficients of the ‘Objective 1’ dummy to be larger with respect to employment in sectors receiving the most support, such as manufacturing, construction and tourism. Conversely, they should be insignificant in sectors not directly supported by the EU Regional Policy (such as agriculture, targeted by other policies, and financial services, less directly related to regional policy support).

Looking at how the impact of the policy in terms of employment varies across sectors could hence help to disentangle that part of employment growth attributable to the policy from that produced by potential external shocks, which could have been driving the employment trend during the period of the analysis independently of policy actions.

The results reported in Table 14 are obtained by re-estimating the analysis in a panel setting where the *i, j* dimensions stand respectively for: *i*) 5 relevant macro-sectors of the local economic structure and *j*) municipalities.¹³ The empirical evidence is totally in line with what it is expected according to policy structure and its aims. The effect of the *policy* on employment variation is positive only for those sectors that have been more directly and explicitly supported by the policy. Instead, no significant impact is found for the ‘control’ sectors (agricultural and financial services).

Table 14 here

Apart from confirming the robustness of the results to macro shocks, this finding suggests that policy-sustained employment growth is mainly concentrated in those sectors with close links to a sustainable local economic development process. This is completely in line with the rationale of the EU Regional Policy. This policy wants to make disadvantaged regions capable of finding their own way towards growth in the context of an on-going process of EU integration. Leveraging regional comparative advantages in sectors particularly suitable for the promotion of such broad development is line with this objective.

7. Conclusions

This paper has contributed to the assessment of the impact of the EU Regional Policy by adapting experimental methods to a non-randomized scenario through treatment effect methods based on an innovative spatial approach. The ‘Spatial Regression Discontinuity’ Model adopted provided us with consistent and unbiased evidence on the Regional Policy’s by estimating its impact in an ‘as good as

¹³ Since the *policy* dummy does not vary within sectors (‘sector-invariant’), the Panel is estimated with a Random Effect specification.

random' scenario in which endogeneity is fully accounted for. The analysis, which ultimately captures the policy effect by defining and comparing randomly defined treatment and control groups, has been developed over some key steps. In particular, it first identified the threshold that determines the treatment discontinuity in the 'policy-change boundary' as the conditioning factor for the treatment that sharply divides observations into treated (they got the 'Objective 1' Status) and untreated (they are refused the status). Then, in order to be able to apply the properties of 'randomized experiment', and by restricting the focus to the observations increasingly closer to the 'policy-change boundary' (the discontinuity), an 'as good as random' sub-sample of observations was identified that includes the municipalities contiguous to the 'policy-change boundary', both treated and untreated (observations 'on' the threshold). Within this sub-sample, observations turned out to be randomly characterized in terms of both treatment and observable and unobservable contextual aspects. By exploiting the fact that municipalities within the sub-sample are more similar to each other than all municipalities, it was proven that everything in the sub-sample (control and contextual conditions) is smoothly distributed across municipalities apart from treatment, which, consequently, is uncorrelated to anything else. As the discontinuity refers only to the *policy*, 'non-Objective 1' observations (untreated) turned out to have (except for treatment) the same characteristics as 'Objective 1', which hence represents the policy 'counterfactual'. By comparing the randomly distributed treatment and counterfactual observations the RDD was finally able to ascribe any discontinuities found in the outcome variables to the only discontinuity that differentiated the two groups: the EU Regional Policy treatment.

The consistent and unbiased RDD analysis estimated a net positive impact of the EU Regional Policy on employment in 'Objective 1' Italian regions. The results' 'internal validity' was confirmed by several robustness checks whereas their 'external validity' was checked by examining the Spanish case.

According to the RDD extensions proposed, moreover, the effect on employment supported by the EU Regional Policy is not only positive but also grounded on specific sectors and on localized development processes. Employment growth has leveraged sectors closely linked to local economic development (i.e. manufacturing, construction and tourism), which are those targeted by the policy. In addition, the territorial cohesion promoted did not imply the displacement of the economic activities from the richest to the poorest areas. Instead, it has promoted its own process of job creation in one of the most persistent scenario of underdevelopment (i.e. the 'Southern Italy') in Europe.

Finally, in addition to providing consistent, unbiased and significant items of evidence of Regional Policy's positive impact, the analysis pointed out how treatment effects methods are a valuable tool in dealing with the endogeneity that is likely to affect the evaluation of the EU Regional Policy. In fact the RDD results obtained here are in contrast to those obtained from the basic OLS models, which do not clean the effect of the *policy* from omitted variables and reverse causality bias, leading to conclude for a negative policy impact.

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Appendix A

Figure A-1. Italy, whole and sub samples.

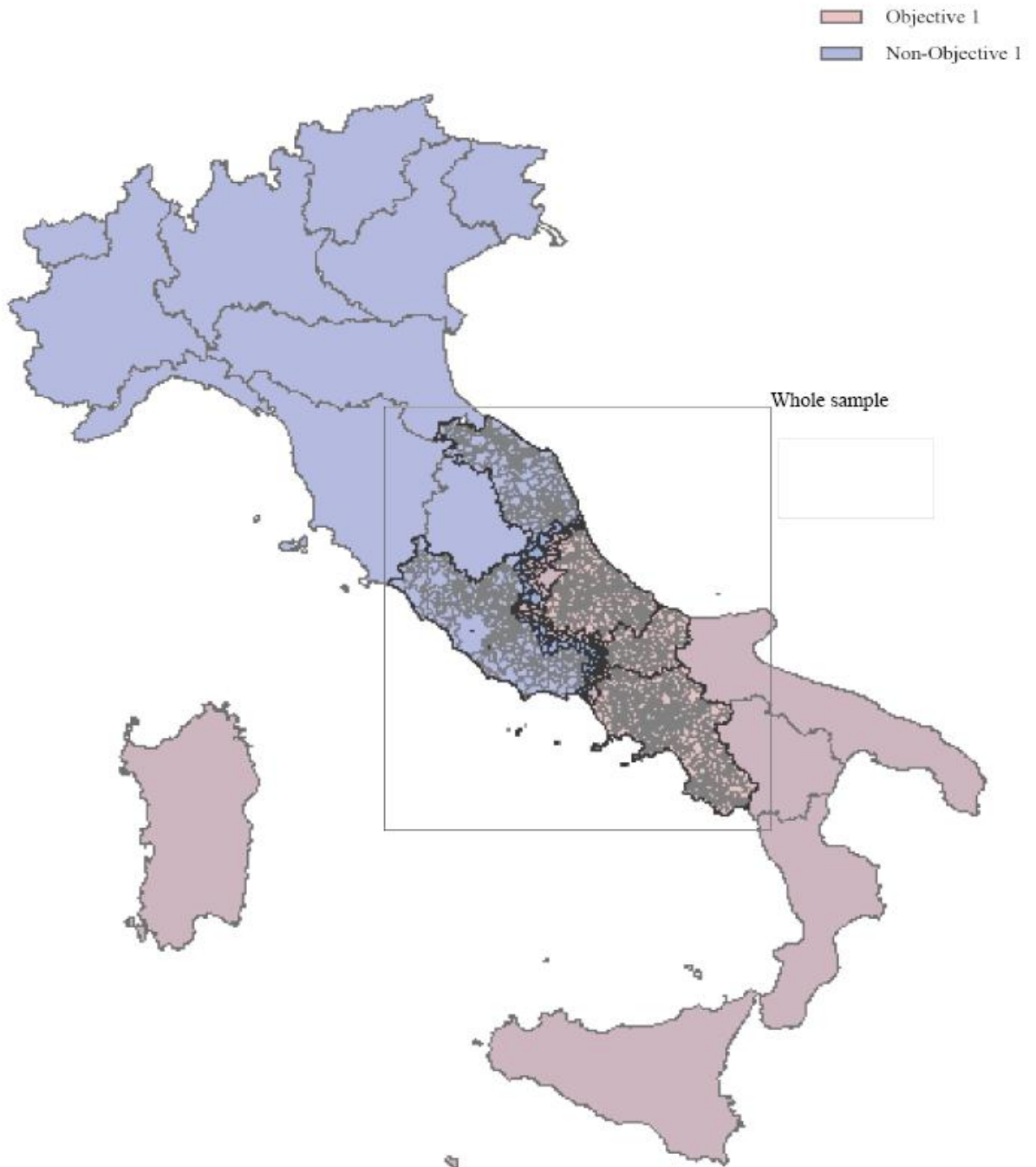


Figure A-2. Whole and sub samples.

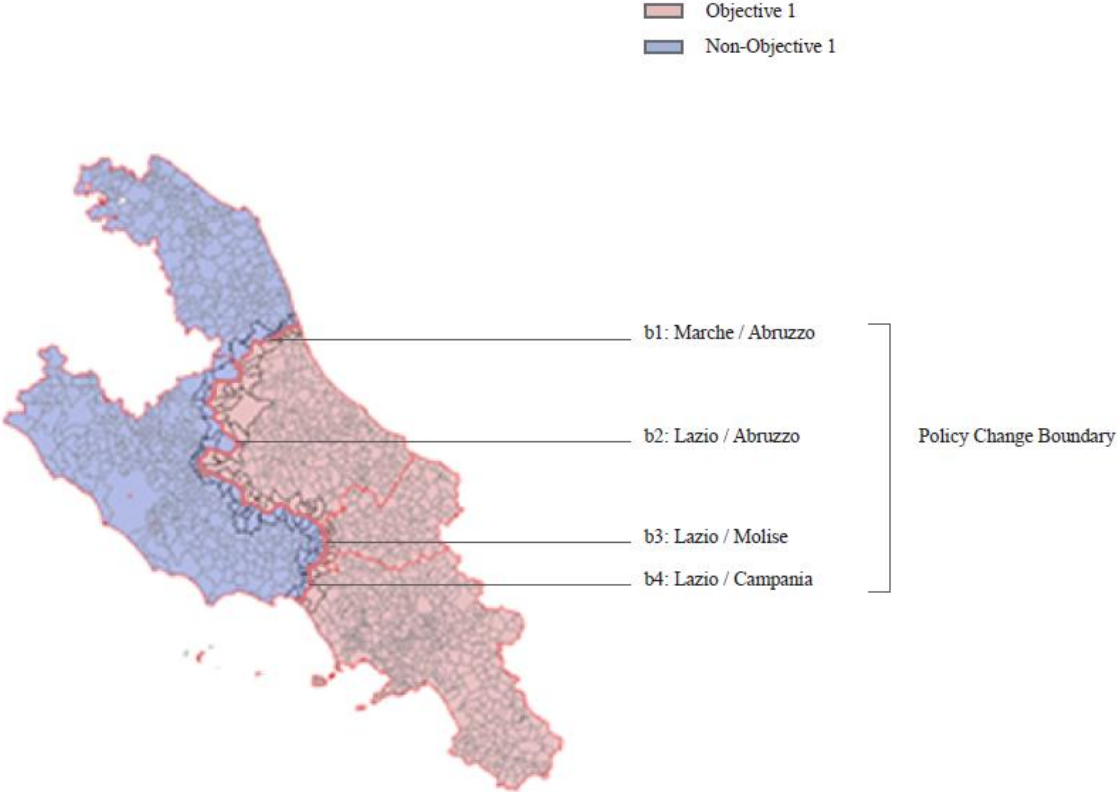


Table 1. Differences in mean for the observable variables in whole and sub samples.

	Whole-Sample			Sub-Sample		
	Objective 1	Non Objective 1	Diff	Objective 1	Non Objective 1	Diff
Dependency ratio	57.13	54.37	-2.75***	59.62	59.41	-0.21
Old population ratio	18.45	19.63	1.17**	21.19	21.48	0.29
Uneducated population	5.33	2.70	-2.63***	3.25	3.46	0.20
Highly Educated pop.	2.05	2.04	-0.01	1.84	1.92	0.08
Regional Transfers	2411,9	3684,2	1272,2	1172,8	1640,0	467,2
Employment	1662.61	3331.91	1669.29	1361.08	1774.51	413.43
Plants	384.22	646.46	262.24*	287.85	436.51	148.66

Table 2. Relation of EU Regional Policy with observables.

	Population density	Dependency ratio	Old population ratio	Uneducated Population	Highly Educated Population
'Objective 1' status	-55.4045 (33.5828)	-1.0886 (1.6924)	-1.0832 (1.0996)	-0.1372 (0.3791)	-0.0407 (0.2224)
R squared	0.354	0.273	0.237	0.179	0.059
Obs	99	99	99	99	99

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Set of boundary dummies included in the models. Robust and clustered S.E. in parentheses.

Table 3. Localized expenditure in the 'Objective 1' municipalities during the policy period 2000-2006.

	Whole-sample (992 municipalities)	Sub-sample (47 municipalities)
Number of Municipalities effectively treated	971/992	47/47
Total expenditure (Billions of Euro)	10,8	0,2

Table 4. Effect of EU Regional policy on employment.

	OLS		RDD	
‘Objective 1’ status	-1.5399 (1.6039)	1.8806 (1.8416)	15.1895** (6.9830)	14.3379** (7.3174)
Employment	-0.0017*** (0.0003)	-0.0004 (0.0003)	0.0006 (0.0013)	0.0004 (0.0031)
Plants	0.0119*** (0.0025)	0.0028 (0.0021)	-0.0013 (0.0077)	-0.0017 (0.0203)
Population density		0.0012 (0.0008)		-0.0051 (0.0334)
Dependency ratio		-0.5918*** (0.0831)		-0.6117 (0.4031)
Uneducated Population		-1.3009*** (0.3001)		1.3459 (1.7686)
Constant	0.6868 (1.2824)	37.5634*** (4.5799)	-14.7111 (10.7885)	23.5980 (31.9162)
R squared	0.010	0.066	0.120	0.146
Obs	1613	1613	99	99

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Set of boundary dummies included in the model. Robust and clustered S.E. in parentheses.

Table 5. Effect of EU Regional Policy on employment (Classic RDD specification).

Polynomial degree	0		1		2	
'Objective 1' status	-1.4999 (1.6529)	2.0080 (1.8821)	10.3105*** (2.8915)	9.8785*** (2.8672)	12.1672*** (4.2367)	12.0415*** (4.1892)
Employment	-0.0017*** (0.0003)	-0.0004 (0.0003)	-0.0016*** (0.0003)	-0.0004 (0.0003)	-0.0014*** (0.0003)	-0.0004 (0.0003)
Plants	0.0121*** (0.0026)	0.0030 (0.0022)	0.0113*** (0.0025)	0.0029 (0.0022)	0.0103*** (0.0024)	0.0028 (0.0021)
Population density		0.0012 (0.0008)		0.0013 (0.0008)		0.0012 (0.0008)
Dependency ratio		-0.5882*** (0.0837)		-0.5796*** (0.0845)		-0.5487*** (0.0861)
Uneducated Population		-1.3310*** (0.3012)		-0.8892*** (0.3247)		-0.8672*** (0.3288)
Constant	0.6044 (1.3488)	37.3595*** (4.6195)	-6.3255*** (1.8624)	30.7554*** (4.9977)	-13.5475 (2.5199)	24.0460*** (5.6317)
R squared	0.010	0.066	0.026	0.074	0.037	0.078
Obs	1566	1564	1566	1564	1566	1564

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Robust and clustered S.E. in parentheses.

Table 6. Effect of EU Regional Policy on employment (RDD External validity test).

Polynomial degree	Spain			Italy		
	0	1	2	0	1	2
Objective 1 status	-11.3690*** (1.5781)	10.3285*** (2.3778)	6.9122** (2.7891)	-1.7620 (1.6602)	10.4404*** (2.9036)	11.9754*** (4.2568)
Constant	23.5648*** (1.0573)	10.3947*** (1.5694)	1.8831 (2.0439)	2.6353** (1.1951)	-4.9363 (1.8310)	-12.6259*** (2.5335)
R squared	0.021	0.021	0.031	0.001	0.018	0.031
Obs	5892	5892	5892	1566	1566	1566

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Robust and clustered S.E. in parentheses.

Table 7. Effect of EU Regional Policy on employment. Italian and Spanish observations pooled (Classic RDD specification).

	Polynomial degree		
	0	1	2
Objective 1 Status	-1.2317 (1.3317)	17.1493*** (1.8678)	8.3689*** (1.9566)
Constant	13.4275*** 0.6332	3.5739 (0.5463)	0.4265 (0.4769)
R squared	0.004	0.031	0.043
Obs	7457	7457	7457

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Robust and clustered S.E. in parentheses. Both the treatment and the forcing variables are interacted with a country dummy.

Table 8. Effect of EU Regional Policy on employment for different control samples.

Treated municipalities: within 15 kms from the Boundary			
'Objective 1' status	Polynomial degree		
	0	1	2
Control municipalities band:			
Whole-sample (obs:672)	-16.6885*** (4.5205)	34.1704** (15.6543)	49.5443** (21.6131)
100 kms (obs:589)	-11.1561** (5.3116)	32.2505** (15.2901)	36.4980* (21.5718)
75 kms (obs:528)	-16.6885*** (4.5174)	23.7783** (12.3807)	36.9954* (19.3603)
50 kms (obs:450)	6.1701 (4.0714)	24.1516** (9.6302)	43.2292** (19.4106)
15 kms (obs:235)	6.1701 (4.0752)	25.4722*** (9.7182)	37.3784** (18.8808)

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Robust and clustered S.E. in parentheses. All the specifications include a set of dummies matching the municipalities by band of belonging.

Table 9. Long run effect of EU Regional Policy on employment (RDD).

	Y: employment variation 91-11
'Objective 1' status	14.033** (6.9878)
Employment	-0.0021 (0.0025)
Plants	0.0140 (0.0158)
Constant	-51.7775*** (7.7872)
R squared	0.143
Obs	99

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Set of boundary dummies included in the model. Robust and clustered S.E. in parentheses.

Table 10. Effect of EU Regional Policy on employment in a Pre Treatment period (RDD).

	Y: employment variation 81-91	Y: employment variation 71-81
'Objective 1' status	25.9492 (20.6554)	-3.5012 (14.9115)
Employment	0.0263 (0.0165)	0.0075 (0.0120)
Plants	-0.1354* (0.0706)	-0.0460 (0.0594)
Constant	61.6136 (52.0853)	17.4320 (14.4474)
R squared	0.124	0.017
Obs	99	99

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Set of boundary dummies included in the model. Robust and clustered S.E. in parentheses.

Table 11. Effect of EU Regional Policy on employment within control municipalities (RDD shifting boundary test).

	Y: employment variation	
Mock 'Objective 1' status	-7.6773 (5.4405)	6.8059 (5.1003)
Employment	-0.0009 (0.0014)	-0.0002 (0.0015)
Plants	0.0113 (0.0088)	0.0006 (0.0103)
Population density		0.0166 (0.0198)
Dependency ratio		-0.5901 (0.3594)
Uneducated Population		0.3103 (1.5174)
Constant	-9.4737 (7.1184)	18.6989 (24.4286)
R squared	0.058	0.128
Obs	110	110

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Set of boundary dummies included in the model. Robust and clustered S.E. in parentheses. The 'policy-change boundary' is shifted within the control regions using municipalities boundaries. The municipalities of control regions that are contiguous to the true 'policy-change boundary' received the treated status. Municipalities of control regions contiguous to these mock treated municipalities are the counterfactual group. The sub-sample is composed by 110 contiguous municipalities.

Table 12. Effect of EU Regional Policy on employment (RDD mock discontinuity test).

	Y: employment variation	
Mock 'Objective 1' status	-4.2441 (10.0908)	-4.8668 (9.5159)
Employment	0.0071 (0.0058)	0.0090 (0.0216)
Plants	-0.0444 (0.0480)	-0.0530 (0.0886)
Population density		-0.0188 (0.1493)
Dependency ratio		-.1270 (0.9270)
Uneducated Population		-0.8489 (0.8886)
Constant	-3.6424 (8.5305)	11.3494 (59.9173)
R squared	0.033	0.039
Obs	68	68

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Set of boundary dummies included in the model. Robust and clustered S.E. in parentheses. The administrative boundary between Campania and Molise is taken here as mock 'policy-change boundary'. The sub-sample is composed by 68 contiguous municipalities. Region of Molise is considered as control.

Table 13. Effect of “Transfers” (in place of EU Regional Policy) on employment (RDD).

	Y: employment variation	
Regional Transfers	0.0000 (0.0000)	0.0000 (0.0000)
Employment	0.0020 (0.0054)	0.0017 (0.0054)
Plants	-0.0063 (0.0095)	-0.0017 (0.0188)
Population density		-0.0187 (0.0319)
Dependency ratio		-0.7237* (0.3996)
Uneducated Population		1.0591 (1.7452)
Constant	-4.8569 (11.5788)	42.2816 (29.8296)
R squared	0.075	0.108
Obs	99	99

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Set of boundary dummies included in the model. Robust and clustered S.E. in parentheses.

Table 14. Effect of EU Regional Policy on sector employment (Classical RDD specification, Panel).

‘Objective 1 Status’	Polynomial degree		
	0	1	2
Agricultural sector	14.0758 (32.6997)	36.1015 (31.2253)	24.7990 (26.9216)
Manufacturing sector	24.2512*** (7.7619)	44.8405*** (9.2313)	32.9690*** (12.7079)
Construction sector	-0.8539 (7.4494)	19.5238* (10.3387)	7.5788 (13.6153)
Tourism sector	13.1202*** (4.4882)	33.4089*** (7.6402)	21.3750* (12.3069)
Financial sector	-22.3071 (7.4423)	-0.1794 (10.3370)	-12.4877 (14.5124)
Constant	50.4067*** (6.5065)	35.1246*** (8.7714)	22.2569** (10.8916)
R squared	0.004	0.005	0.007
N	6696	6696	6696

***statistically significant at 1% level; ** statistically significant at 5% level; *statistically significant at 10% level. Clustered S.E. in parentheses. All the specifications include the sector dummies.