Spatial Effects in Evaluating the Impact of European Regional Policy

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1. Introduction

The **European regional policy (ERP)** is a natural field of interest to study the effects of regional policies: ERP is the wider and probably longer experiment of income redistribution across regions and countries. The policy is devoted to the reduction of economic and social disparities between regions. Each EU country makes yearly transfers of about 1% of own national GDP to the European Union, and receives a variable share of these founds, depending on regional wealth and disparity with European average per capita income. Moreover, there is not only a academic interest in evaluating the policy: both policy makers and citizens are interested in knowing the effects of ERP, in reason of the huge amount of financial resources dedicated to European regional intervention

Many scholars have assessed the **impact of European regional policy** on regional growth and employment. However, the capacity of the policy to promote regional economic growth remains controversial, and the evaluation exercises are not unanimous about its impact on European regional development (Dall'erba and Fang, 2017, Fiaschi et al, 2017 for a recent review). Only few papers, among many, are based on the counterfactual approach that, in our opinion, enables a more precise identification of the effects of the policy, regardless of the choice of the transmission channels through which the policy operates.

Another aspect that is usually neglected in these studies is the presence of spatial externalities; regional policies are designed to boost growth, employment and investment and generate spillovers between firms, industries and territories. In this perspective, the role of neighbors becomes crucial when we want to estimate the impact of the policy. Therefore, the evaluation of European regional policy has to take into account properly the spatial dimension of these effects. This is the approach we used in this paper. The aim is to assess the regional impact of the policy in a counterfactual robust framework, analyzing simultaneously direct and indirect effects, originating from spatially neighboring regions.

Regional economic development depends not only on the regional characteristics of production factors, but also on the features of neighboring regions, the spatial connectivity structure of the regions, and the strength of spatial dependence (LeSage and Fischer, 2008; LeSage and Pace, 2009, Pieńkowski and Berkowitz, 2015). Generally, the presence of a spatial interaction implies that subsidies in a region affect also contiguous regions. In this case, the standard method used for the counterfactual evaluation cannot be used: the stable unit treatment value assumption (SUTVA) in the Rubin model is not valid and other econometric evaluation methods should be used in order to detect the consistent policy impact in the presence of spatial dependence. (Cerulli, 2015; De Castris and Pellegrini, 2015).

The intensity of the European regional policy is strongly heterogeneous across regions and countries (Cerqua and Pellegrini, forthcoming). However, even if Structural Funds payments should be the main variable of interest in the evaluation of Structural Funds regional impact, several studies in the literature use only a binary variable, indicating whether a given region is eligible for Structural Funds transfers or not. Actually, the use of dummy variables for Structural Funds payments neglects substantial differences in aid intensities between regions. The difference in regional EU transfers intensity is large: it varied from below 1 % of GDP in some Objective 1 regions to above 10 % in the others (Pieńkowski and Berkowitz, 2015).

The heterogeneity of Structural Funds intensity values by regions is depicted in the following map, related to the Structural Funds transfer payments per capita in the period 2000-2006. We consider NUTS2 regions that refers to EU15 countries excluding over-seas territories and including Eastern Germany. The NUTS classification refers to the administrative configuration of the year 2006.

[insert figure 1]

Moreover, if regions are clustered into more developed areas and less developed areas, the effects of neighbors' spillover reinforce cluster differences. This is particularly true in many areas of Southern Europe, such as the Mezzogiorno in Italy, where there is an agglomeration of areas with low productivity, high unemployment, low levels of education, low income, especially if compared to the rest of the country. It follows that spatial effects reinforce the difficulties in development and thus those of convergence with the rest of Europe.

The use of counterfactual methods for evaluating European regional policy is very recent. These papers are based on the Rubin Causal Model (Rubin, 1974) which explicitly excludes interference among treated and not treated units. The presence of a spatial interaction implies that subsidies in a region also affect contiguous regions. In this case, the stable unit treatment value assumption (SUTVA) in the Rubin model is not valid and other econometric evaluation methods should be used in order to detect a consistent policy impact in the presence of spatial dependence. (Cerulli, 2015; De Castris and Pellegrini, 2015).

The traditional approach to evaluate policy effect in a counterfactual framework using a continuous treatment is the "generalized propensity score" or GPS (see Becker, 2012 for the case of Structural Funds). The GPS method allows the estimation of a Dose-Response Function (Hirano and Imbens, 2004; Imai and Van Dyk (2004); Flores et al., 2012; Bia and Mattei, 2012, Cerulli, 2012; Bocci and Mariani, 2015, Magrini et al. 2017), where the marginal effect of treatment varies in response to different levels of the same treatment. However GPS faces explicitly selection bias issues but does not control for spillover effects. In presence of spillover effects, even a perfect control of the selection bias is not sufficient to avoid a biased estimate of the policy effect (Cerqua and Pellegrini, 2017). At our knowledge, in the literature there are not evaluation methods that explicitly tackle both issues, i.e. spatial interference among units and continuous treatment.

In this study, we evaluate the impact of European Regional Policy - considering Structural Funds and Cohesion Fund- on regional economic growth in the European Community, in presence of spatial interactions among regions and heterogeneous policy intensity. We propose a new methodology for estimating the unbiased "net" effect of ERP, based on a novel "**spatial GPS" technique that compare treated and not treated regions affected by similar spillovers due to ERP impact.**

The method is based on a modified version of the Spatial propensity score matching proposed in De Castris and Pellegrini (2015). The analysis verifies if the heterogeneous impact of ERP between regions also depends on the intensity of treatment, measured by the amount of funds received by each region normalized to its population.

The results show that spatial spillovers have a significant, even if moderate, effect on regional growth. On average, the net effect of the ERP, excluding the impact of spatial interactions with the neighboring regions, is lower than the gross effect that includes spillovers. The reason is the spatial distribution of ERP. Being the ERP intensity higher among low-income regions and clusters, the spillover effects in these areas are lower than average. Moreover, the impact is non linear, and after a certain intensity threshold, additional transfers are not, on average, associated with significantly higher regional growth. This pattern has relevant policy implications, because it suggests a different way of distributing the policy among regions, taking into account both the intensity of the aid and the agglomeration effects.

The rest of the paper is organized as follows. In the next section, we present a brief summary of the relevant literature regarding the evaluation of ERP considering continuous treatment and spatial spillover. In Section 3, we discuss the econometric methodology applied for the identification of causal effects of the EU's regional transfers on economic growth and in Section 4 the empirical identification and specification of the model. Details on the sources and the construction of data at the NUTS-2 regions level for the two programming periods 1994-1999 and 2000-2006 are in Section 5. We present the results and interpret the findings in Section 6. In Section 7, we use our model to analyze the impact of ERP spillover of lagging regions in Europe. The last section concludes with a summary of the most important findings and some political implications.

2. Literature

The literature on evaluation of the effects of transfer intensity in a counterfactual framework is still scarce. Up to now, we are aware of only four papers. Mohl and Hagen (2010), using a panel approach and NUTS2 grid, show that Objective 1 payments have a positive but not statistically significant impact on the regions GDP growth rate. Two papers are methodologically based on the GPS matching, a non-parametric method to estimate treatment effects conditional on observable determinants of treatment intensity, to assess the effect of the policy. Becker et al. (2010), using a NUTS 3 grid, identify a modest positive impact of Objective 1 transfers on regional growth of GDP per capita, but the marginal impact is nonlinear, and is decreasing after a certain threshold. Becker et al. (2016) investigate the 2007-2013 programming period using several outcome variables, including education and innovation outcomes, and the NUTS2 grid. Their findings are generally positive and suggest that regions generally tend to benefit from balanced funding of activities unless they are extremely specialized ex ante. Cerqua and Pellegrini (forthcoming) exploit a different methodological approach, extending the regression discontinuity analysis to the case of continuous treatment. The results show a positive and statistically significant growth effect of the European regional policy and confirm that the effect of policy intensity can be nonlinear, with marginal effect that is negligible after a given intensity.

These models control for spatial error or spatial autocorrelation, but the SUTVA assumption is used in all the previous analysis. The econometric problem here is not to deal with the traditional assumption of independence (in the space) of the error terms, but with the presence of spatial interference, or spatial spillover, that is not properly captured by a simple spatial econometric model. Therefore, the earlier literature related to the use of spatial econometric model in the evaluation framework (Dall'erba and Le Gallo, 2007, 2008; Bouayad-Agha et al., 2011) is of little help in our case. Our paper is more along the spirit of Arpino and Mattei (2016), where in a counterfactual framework interactions among units are explicitly modeled, considering which firms interact with each other, and the relative magnitudes of these interactions. Another close paper is Cerqua and Pellegrini (2017). They propose a new framework that partially relaxes the SUTVA identifying three groups of firms: treated, non treated and affected (untreated firms that enjoyed externalities from treated firms). Using these groups the paper can detect contemporaneously the direct effects of the regional policy and the indirect (spillover) effects coming from the interaction of firms. These results are achieved on the basis of strict identification assumptions that are quite strong. Our paper is based on a different identification approach that extend the approach used in De Castris and Pellegrini (2015) to the case of continuous treatment. The idea is to compare treated and not treated units subject to similar spillover effects due to treatment, and the difference between treated and not treated outcome identifies the "net" or "direct" treatment effects (i.e., net of spillover). The easiest method is to incorporate the intensity of spillover, and therefore the spatial lag of the characteristics that affect spillovers, in the GPS estimation. Our approach does not involve strong identification assumptions but has a cost: we cannot simultaneously and consistently estimate the spillover effects. Instead, we can only derive them indirectly by comparing the results obtained with the standard approach with those resulting from our method.

3. Relaxing SUTVA in presence of spatial dependence between regions

Our methodological approach is easily described starting from the case of a binary treatment .

Consider a group of regions indexed by i = 1,…, N.

Let be D_i the random variable that denotes a treatment indicator equal to 1 if treatment is received by the region and 0 otherwise.

Let $\boldsymbol{D}$ ≡ (D_1,…, D_i,…,D_N) represent the treatment assignment for all regions.

We describe the potential outcome for region i as a function of the region's own treatment assignment (D_i) and the treatment assignment of other regions ($\boldsymbol{D}_{-i}$). Therefore, for region i the potential outcome is denoted by Y_i ($\boldsymbol{D}$). In this way the potential output of each region is affected by the potential output of all regions. We can consider SUTVA a special case where the potential outcome $Y_i(\boldsymbol{D}) = Y_i(D_i)$.

However, even in this simplified framework a reduction in the complexity of the causal inference framework is needed in order to achieve a solution. The simplifying assumption is that interference in space across region can be described by a *first-order* spatial dependence.

Therefore, adopting the parsimonious parameterization for spatial dependence proposed by Ord (1975), output is described by a *spatial first-order* autoregressive process. Applied to our problem, we have:

(1) $$Y_i(\boldsymbol{D}) = Y_i(D_i, \boldsymbol{w}_i Y_{-i}(\boldsymbol{D}_{-i}))$$

Where w_i is the i-th row of the usual spatial weight matrix W (Le Sage and Pace, 2009). The cross-product $\boldsymbol{w}_i Y_{-i}$ is the spatial lag, representing a linear combination of values of variable y constructed from regions that neighbour observation i.

The present framework allows us to estimate different causal effects; however, we are particularly interested in a specific causal effect, that is the treatment effect for a subsidized region i:

(2) $$Y_i(D_i = 1, w_i Y_{-i}(\boldsymbol{D}_{-i})) - Y_i(D_i = 0, w_i Y_{-i}(\boldsymbol{D}_{-i}))$$

Note that the spillover effects here are equal among the status of treated and the status of not treated. Therefore, the impact of the treatment is estimated without ("net" of) spillover coming from the neighbours.

Because of the fundamental problem of causal inference (Holland, 1986), we consider all the regions to estimate the average treatment effect (ATT):

(3) $$E[Y_i(D_i = 1, w_i Y_{-i}(\boldsymbol{D}_{-i})) - Y_i(D_i = 0, w_i Y_{-i}(\boldsymbol{D}_{-i}))|D]$$

where i= 1,…, N

The counterfactual scenario for the ATT consists of changing the assignment for region i from $D_i = 1$ to $D_i = 0$ without removing the treatment (ERP) to all the other regions in the neighbours of *i*. Therefore, the assumption implies that spillover effects among treated and non treated are equal, and we estimate the net impact, that is cleared from spillover effects. These assumptions will allow us to partially relax the SUTVA. However, the assumption imposes a constrain on the the matching procedure: we have to match regions with similar spatial spillover effects.

This is not the only possible choice. Cerqua and Pellegrini (2017) remove the subsidy from all the other units neighbouring *i*, in the counterfactual scenario, i.e., $\boldsymbol{D}_{-i}$ is changed to the null vector if $\boldsymbol{D}_{-i} \neq \boldsymbol{0}$

Empirically, if we assume that selection on treatment is due to a set of observable pre-treatment characteristics X_i, the estimate of the "net" ATT can be carried out using a nonparametric approach, such as the matching estimator proposed by Rosenbaum and Rubin (1983) and developed in several evaluation papers (see Blundell and Costa Dias, 2008). It relies on the assumption that selection in the intervention is observable, that is, it can be taken into account by conditioning on observed individual characteristics.

A general formulation for the matching estimator ($\boldsymbol{\alpha}_{MM}$) is given by (4):

$$\hat{\alpha}_{MM} = \sum_{i \in S} \left(Y_i^S - \sum_{j \in NS} \omega_{ij} Y_j^{NS} \right) \omega_i \tag{4}$$

As the number of characteristics used in the match increases, the chances of finding a match are reduced. This obstacle is overcome thanks to an important result (Rosenbaum and Rubin, 1983) showing that matching on a single index reflecting the probability of participation achieves consistent estimates of the treatment effect in the same way as matching on all covariates. This index is the Propensity Score (PS), and this variant of matching is well known as "propensity score matching". Any standard probability model can be used to estimate the PS.

$$PS_i = Pr\{D_i = 1 | X_i\} = F(h(X_i)) \tag{5}$$

where $F(.)$ is the normal or the logistic cumulative distribution and $h(X_i)$ is a function of covariates X_i

In presence of spatial interference among units, using the previous assumption, we can define a "spatial" PS (PSspat), that exploits the spatial correlation. The probability of participation is therefore conditioned to the level of spillovers:

$$PSspat = F(h(X), g(w_i Y_{-i}(\boldsymbol{D}_{-i}))) \tag{6}$$

The framework in the case of continuous treatment is more complex. However, we can use similar hypotheses and consider how to change the effect of the treatment in presence of different treatment intensities, maintaining the spatial spillover constant.

The framework in the case of continuous treatment can follow Hong and Raudenbush (2013). The potential outcome for region i is described as a function of the region's own treatment intensity (T_i) and the treatment intensity of other regions ($\mathbf{T}_{-i}$). In this way the potential output of each region is affected by the potential output of all regions, that depends on all the different intensities of treatment.

$$Y_i(\boldsymbol{T}) = Y_i(T_i, \boldsymbol{w}_i Y_{-i}(\boldsymbol{T}_{-i})) \tag{7}$$

Here T_i assumes different values, from 0 to T_{max}

If $T_i > T_j$, the "net" effect of increasing T from T_i to T_j is:

$$E[Y_i(T_i, w_i Y_{-i}(\boldsymbol{T}_{-i})) - Y_i(T_j, w_i Y_{-i}(\boldsymbol{T}_{-i}))|\boldsymbol{T}] \tag{8}$$

The estimation of (8) is not easy. In absence of interference, the traditional approach is based on the Generalized Propensity Score, proposed by Hirano and Imbens in 2004. Given X_i a vector of pre-treatment covariates and being T_i the level of received financial resources by ERP, the value of the potential outcome corresponding to this treatment level is:

$$Y_i = Y_i(T_i) \tag{9}$$

Let r the conditional density of the treatment given the covariates $\boldsymbol{X}$ and the treatment T:

$$r(T; X) = f_{T|X}(T|X) \tag{10}$$

The generalized propensity score is defined by $R = r(T;X)$. However, if we introduce spatial interference, we have to consider the spillovers. Also in the case of GPS we pair units with the same spillovers, that means with neighbors with the same level of covariates.

We define a novel estimator, the "*spatial*" GPS, where the value of the GPS for each region depends also on the outcome and covariates of neighboring:

$$(11) \qquad R = r(T;X;wX)$$

A key assumption, weak uncounfoundedness assumption, is made, in order to adjust for systematic differences between groups receiving different levels of the treatment in a set of pre-treatment variables.

$$(12) \qquad Y(T) \perp T \mid X, wX \text{ for all } t \in T.$$

So adjusting for observed covariates is sufficient to achieve independence between potential outcomes and the treatment level received. The GPS adjusts for a one-dimensional score. It is like a balancing score as defined by Rosenbaum and Rubin (1983), within strata with the same value of r(t; X), the probability that T is equal to a given level T does not depend on the value of X. In our case we add a new dimension (the covariates of the neighbors) and the probability that T is equal to a given level T does not depend on the value of X and on the covariates of the neighbors.

4. Empirical strategy

Let be: Y a continuous variable, the outcome, in our case the regional growth; T is a continuous treatment variable, the amount of Structural Funds transfer; GPS, the generalized propensity score, that is equal to r(T,X, wX).

The conditional expectation of the outcome is equal to:

$$(13) \qquad E[Y|T=t, R=r] = E[Y(t)|\, r(t,X)=r\,] = \beta(t,r)$$

and it is estimated as a function of a specific level of contribution and of a specific value of GPS, R = r .

In this approach β(t,r) does not have a causal interpretation.

The probability of the observed treatments - being equal to some potential treatment combination - is independent of the covariates in X_i once we have conditioned on the GPS.

We then average out the conditional expectation over the marginal distribution r(t,X):

$$(14) \quad \mu(t) = E[E[Y(t) \mid r(t,X)]]$$

to get the average dose-response in order to estimate the causal effect as a comparison of μ(t) for different values of t. In our application we specified a cubic approximation in the model.

$$(15) \quad E[Y|T;R] = \alpha_0 + \alpha_1 T + \alpha_2 T^2 + \alpha_3 T^3 + \alpha_4 R + \alpha_5 R^2 + \alpha_6 R^3 + \alpha_7 T R$$

5. Data

We use an integrated dataset, including European data on Structural Funds and Cohesion Fund payments for the period 2000-2006 by NUTS2 and longitudinal information on economic and demographic characteristic of the regions. Our sample consists of 200 regions that refer to EU15 countries excluding overseas territories and including Eastern Germany. We consider a large variety of covariates to describe the level of regional welfare before and after the policy's period: GDP at purchasing power parity (PPP), employment, population, and investment at the level of NUTS2, education by level, and regional indicators on structural dimension. The treatment variable, i.e. the dose, is defined as the transfer payments to each region in the period 2000-2006, in percent of the region's population.

Variables used in the specification of the outcome regression model.

Covariates	***Definition***
Treatment level (thousand per capita)	Per capita yearly fund (continuous variable)
Population density	Inhabitants per square kilometre (thousand)
Low skilled human capital (share)	Share of low educated people (primary education)
High skilled human capital (share)	Share of high educated people (tertiary education)
Economic level before the policy	Gross Domestic Product per capita, year 1998
Primary sector (share)	Share of agriculture employment in 1998
Tertiary sectory	Share of service employment in 1998
Fixed Capital	Gross Fixed Capital Formation
Treatment volume Spillover	Spatial lag of yearly public fund
Neighbourhood contest: Service	Spatial lag service
High human capital Spillover	Spatial lag share of high educated people
Fixed Capital Spillover	Spatial lag Fixed Capital
Dummy: regions over 300 euros	Regions with per capita yearly treatment > 300
Outcomes	
GDP per capita (PPP) growth rate	Gross Domestic Product on a purchasing power parity basis divided by population, growth rate period 1999-2007

We take into account the **spatial dependence** between regions, in order to estimate a spatial generalized propensity score. We introduce a spatial weights matrix W based on the binary contiguity of the spatial regions, in this way we capture spatial interactions under consideration in our model: treatment spillover and economic spillovers. Regions are determined to be 'contiguous' if the distance between centroid is lesser than 350 km. W is a symmetric matrix, with '0's along the diagonal. We can calculate the spatial lag of the treatment variable and of different covariates: investment, employment, high education in the year 2000, before the starting of the program.

6. Results

We estimate the dose-response functions using the approach developed by Bia and Mattei (2008) (updated version). The estimation of "non spatial" GPS includes several covariates (population density, share of low skilled human capital, share of high skilled human capital, GDP per capita before the policy, share of primary sector, share of tertiary sector) that have the expected sign and are statistically significant. In the estimation of the "spatial" GPS we also include the spatial lag of yearly public fund, service sector, share of high educated people, fixed capital. The result of the estimation are in the table 1 and 2.

Estimating a generalized propensity score, we construct the two dose response function (Figures 2 and 3) and the corresponding marginal treated effects, in the two cases, with and without interference.

The analysis can be focused on these graphs. In both cases the dose-response functions are non-linear, close to a parabolic function with a maximum around 1.5 in the case of interference, higher in the case without interference. However, the marginal effects cross the zero line around the treatment level 1.2 in both cases. For different treatment percentiles the marginal effects are always higher in the case with interference than in the case without interference, even the difference is lower than the standard error.

The conclusion is that the effect in the case with interference is higher than in the case without interference, suggesting that the spillover are negative even if non always statistically significant.

[Figure 2 about here]

[Figure 3 about here]

[Figure 4 about here]

[Figure 5 about here]

Table 1- Marginal effects of the European Regional policy treatment

		Marginal effects without interference		Marginal effects with interference	
Treatment Percentile	*Treatment Intensity*	*dy/dT*	*Std error*	*dy/dT*	*dy/dT*
1st	9.5	-.000220	.000574	-.000240	.0005479
5th	12.8	-.000181	.000543	-.000197	.0005194
10th	14.7	-.000159	.000526	-.000172	.0005033
25th	22.4	-.000075	.000458	-.000077	.0004415
50th	32.1	.000023	.000381	.000033	.0003695
75th	85.1	.000411	.000155	.000470	.0001346
90th	208.4	.000336	.000249	.000440	.0002318
95th	253.7	-.000035	.000240	.000047	.0002550

7. Neighbour effects in low-income clusters: the case of the Southern European Regions

In order to show the neighbor effects in European regions that are characterized by low income, we consider, along the two programming periods 1994-1999 and 2000-2007, Objective 1 regions of five countries Portugal, Spain , Italy, France, Greece. However, we exclude overseas territories, and therefore France is not in the group. Considering the spatial distribution of the remaining Southern European Regions (SER), 3 main clusters are observed (South Spain and Portugal, Mezzogiorno, South Greece), characterized by low-income regions with low-income neighbors.

Table 2: Southern European Regions in our analysis

Country	Number of regions
Italy	8
Spain	8
Portugal	4
Greece	13

Table 3. Main variables for southern regions and all the other ones

	Others	SER
N. regions	167	33
GDP per capita 1988	25534	14623 (57%)
Population Average	1879	1821
Area square km	14970	21801
Per capita Structural Funds	**41**	**215**
Structural variables.		
Population over 65	14.6	16.9
Share of agricultural worker	3.4	15.5
Employment rate	65.6	53.9
Education ratio (Low/High)	0.9	2.7
GDP growth 1994-99	2.5	2.6
GDP growth 2000-07	1.6	2.0
GDP growth 2007-2011	-0.3	-3.0

Table 4 **Differences in the neighbours' covariates of our sample of SER**

Spatial lag variables (neighbors)	**Others**	**SER**
GDP pc 1988	24940	18728 (75%)
Per capita ERP	50	165
Fixed investment	10971	10668
High education	21.8	17.9

Therefore, the analysis of the neighbor's effects in these clusters is very substantial, in order to assess the size and the role of the estimated spillover effects. In this example we demonstrate that the size of spillover's effect in the Southern European regions is relevant and it is an important dimension of the growth effect of SF.

We define the spillover effect as the difference between gross marginal effects and net marginal effects. The gross marginal effect is represented by the marginal effect we can detect when we estimate the impact of the treatment without controlling for what happens in neighboring regions, so we do not match the treated regions with its neighbors. The net marginal effect, on the contrary, is the estimated marginal effect when we match with neighbors of the treated region.

For a given level of the treatment, the effect of the policy on GDP growth rate is the product between the amount of funds per capita (t) and the marginal effect (dy/dt)

*(16) Effect on growth rate = t * dy/dt*

(17) Spillover effects = Effect on growth rate with interference - Effect on growth rate without interference

In the following table we represent an empirical case considering the 90^{th} percentile of the distribution of the treatment for Structural Funds and Cohesion Fund in the period 2000-2006. The percentile is associated with the value of 215, close to the amount of per capita per year SF in SER (see tav. 3). The marginal effects are in table 1. The final results are in table 5: the net effect is higher than the gross effect. The difference is equal to -2.3% cumulated in the period, almost one third of the total gross effect.

Table 5 – Computation of spillover effects

Interference	Type of Marginal effect	Estimated Marginal effect (a)	Fund per capita	Effect on GDP growth rate per capita 1999-2007
No	gross	0.0004402	215	7.2%
Yes	net	0.000336	215	9.5%
Spillover effects	gross - net			-2.3%
Yearly Spillover effects				-0.3%

7. Conclusions

The analysis shows how a major attention to the role of spatial spillover effects can shed new insights into the measure of the impact of ERP. The results prove that the dose-response function of treatment intensity on the regional growth is non linear and is negative (not statistically significant) for very low and very high level of regional transfers, in line with Becker (2010) and Cerqua and Pellegrini (forthcoming).

Moreover, the data suggest that the NUTS2 regions with lower levels of funds show a larger impact on GDP per head than the NUTS2 regions with higher levels of funds. After a certain intensity threshold, additional public transfers are not, on average, associated with significantly higher regional GDP growth rate.

Around the average level of per capita SF in Southern European Regions (the Objective 1 regions), the dose-response function is positive and statistically significant; the impact of ERP is for the average region positive, and reduces regional disparities.

However, the net effect of the ERP, considering the interactions with the neighboring regions, is for those regions marginally higher than the gross, effective impact of ERP on GDP growth. Therefore, spatial spillovers are lower than the average. The reason is that the SER are mainly in a spatial cluster of less developed regions, and the spatial interactions have only a less-than-average impact on the neighbors' growth.

Spatial spillovers across regions appear to be an important multiplicative factor that increase (or decrease) the average impact of the European Regional Policy but also increase (or decrease) the impact heterogeneity between regions with a different level of per capita GDP.

From the policymakers point of view, the conclusion is that the positive impact for growth and convergence in Europe coming from the ERP is mitigated by both an excessive level of ERP for some (few) regions and the presence of negative spillover effects between contiguous low-income regions.

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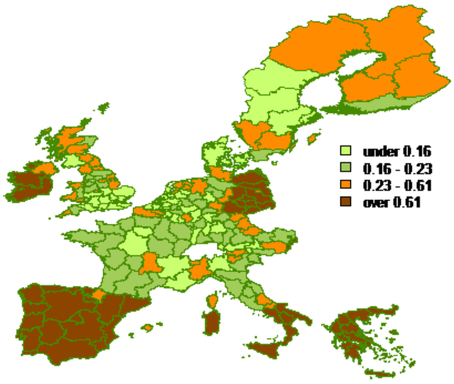
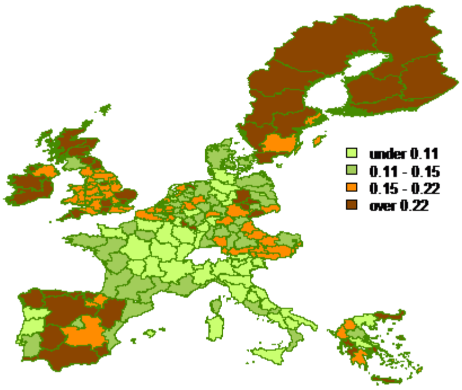
APPENDIX

Figure 1. Geographical distribution of European regional policy intensity in the period 2000-2006. Structural Funds transfer payments per capita. NUTS Classification 2006.



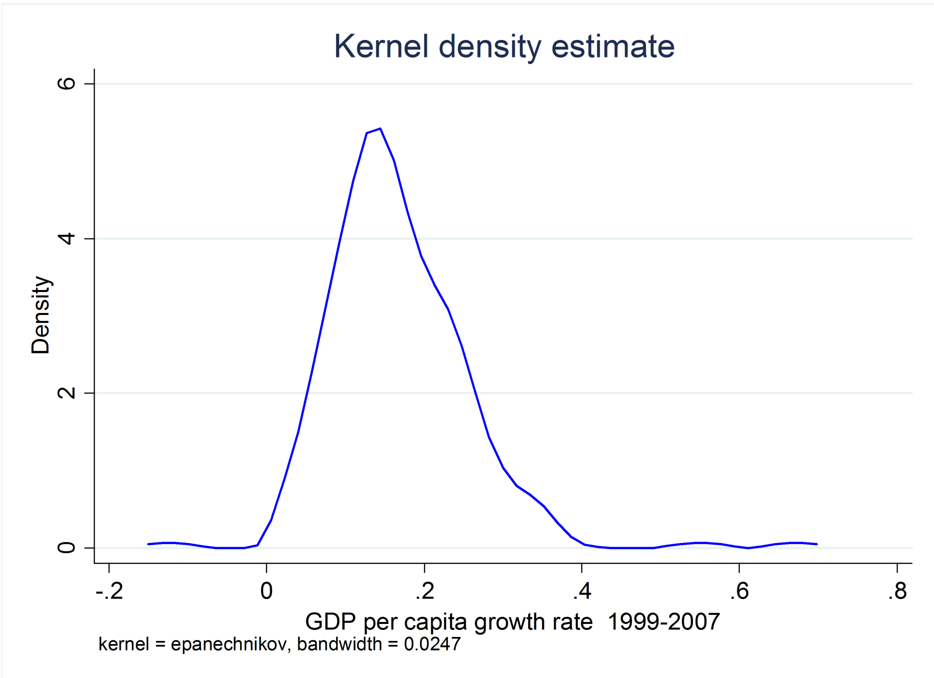
Source: Our calculations on data of European Commission.

Figure 2- Geographical distribution of per capita GDP growth rate by regions (1999-2007).



Source: Our calculations on data of European Commission.

Figure 3- Outcome distribution GDP per capita growth rate 1999-2007



Source: Our calculations on data of European Commission.

Figure 4 – Estimates without interference

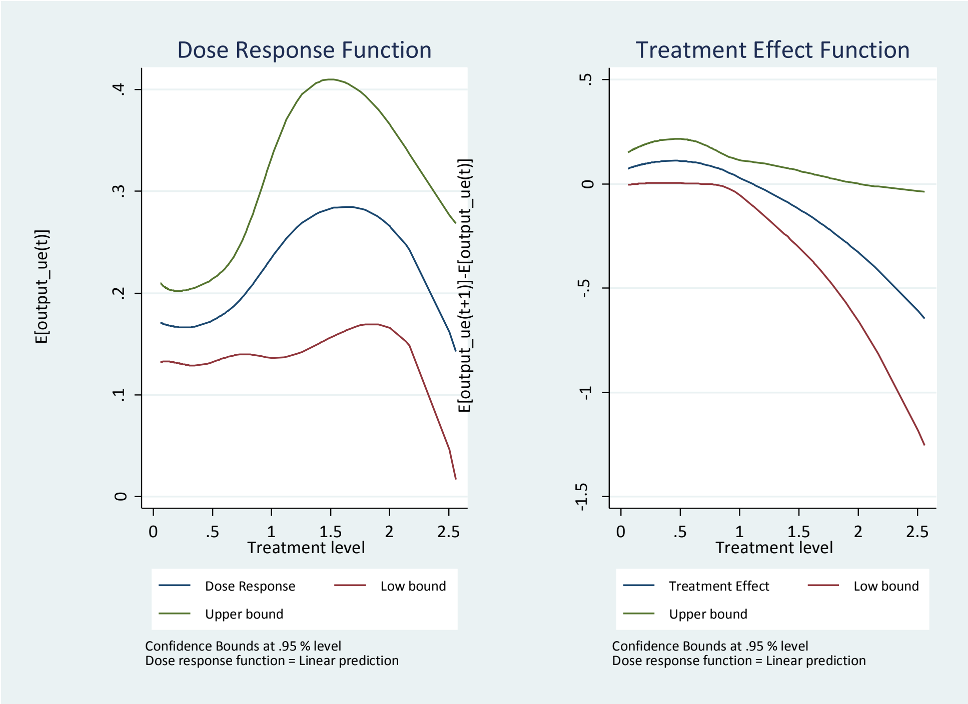


Figure 5 – Estimates with interference