Assessing the impact of spillover effects in European Regional Policy: evidence from Southern regions

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Assessing the impact of spillover effects in European Regional Policy: evidence from Southern regions

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The European Regional Policy (ERP) sustains regional growth by developing demand, supply and technology spillovers between firms and regions. A correct evaluation of the ERP must therefore include the spatial dimension of the effects of the policy.

This is the approach used in this dossier, which analyses the impact of ERP on regional economic growth in the EU15 area, also considering the effect of spatial interactions between regions. An innovative econometric methodology is proposed, based on the Spatial Generalized Propensity Score, which allows to identify the "net" effect of the ERP, with or without spatial spillovers, also taking into account the geographical differences in the intensity of the policy.

The results show that the effect of the regional policy is higher if spatial interactions between regions are also included. These spillovers tend to amplify the impact of the ERP on the basis of the economic capacity of neighbouring regions. It follows that in regions within poor areas spillovers are below average.

La Politica Regionale Europea (ERP) aiuta la crescita regionale anche sviluppando spillover di domanda, di offerta e tecnologici tra imprese e territori. Una valutazione corretta dell'ERP deve quindi includere la dimensione spaziale degli effetti della politica.

Questo è l'approccio utilizzato in questo dossier, che analizza l'impatto dell'ERP sulla crescita economica regionale nell'area EU15, considerando anche l'effetto delle interazioni territoriali tra regioni. Viene proposta una metodologia econometrica innovativa, basata sul Generalized Propensity Score Spaziale, che permette di identificare l'effetto "netto" della ERP, con o senza gli spillover spaziali, tenendo conto anche delle diversità geografiche dell'intensità della politica.

I risultati mostrano che l'effetto è più elevato se si includono anche le interazioni spaziali tra regioni. Tali spillover tendono ad amplificare l'impatto dell'ERP sulla base della capacità economica delle regioni vicine. Ne consegue che nelle regioni in aree povere gli spillover risultano inferiori alla media.

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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 an academic interest in evaluating the policy: both policy makers and citizens are interested in knowing the effects of ERP, in reason of the **large 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., 2018, Crescenzi and Giua, 2020).

A strand of the literature focusses on many aspects that can modify the impact of ERP, such as geographical characteristics of the recipients (Gagliardi and Percoco, 2017), the local context (Bachtrögler et al, 2020, Di Caro, Fratesi, 2022), and the local quality of government (Accetturo et al, 2014).

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.

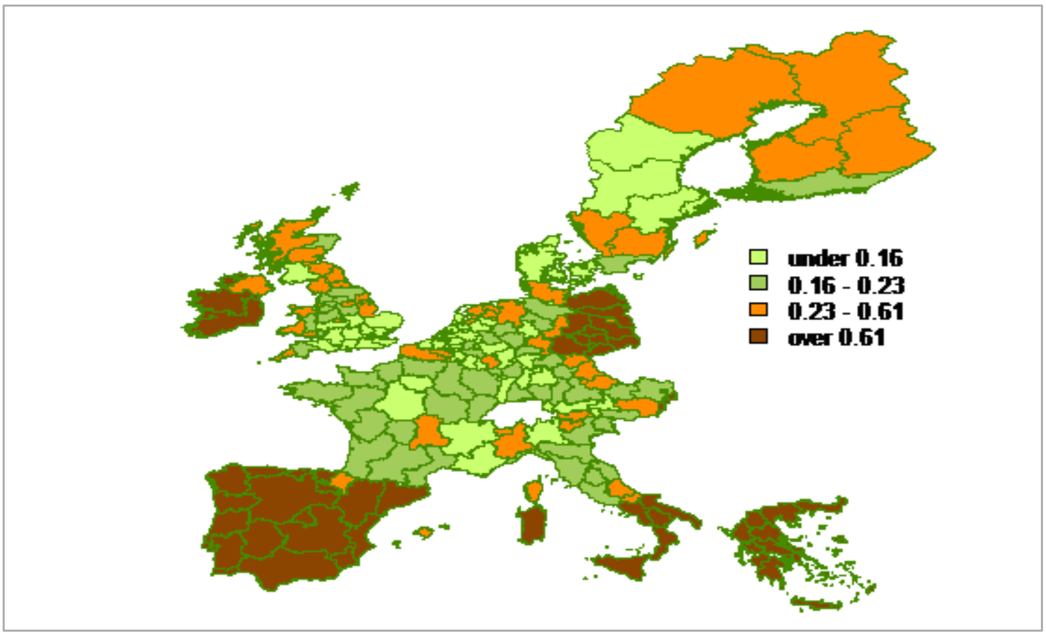
Regional economic development depends not only on the regional characteristics of production factors, but also on the **features of neighboring regions**, the **spatial connectivity**

structure of the regions (Elhorst, 2010), and the **strength of spatial dependence** (LeSage and Fischer, 2008; Pieńkowski and Berkowitz, 2015). Generally, the presence of a spatial interaction implies that subsidies in a region also affect contiguous regions. In this case, the standard model applied for the counterfactual evaluation cannot be used: the stable unit treatment value assumption (SUTVA), crucial 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, De Castris and Pellegrini, 2019).

The intensity of the European regional policy is strongly heterogeneous across regions and countries (Cerqua and Pellegrini, 2018). 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 huge: 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, representing the Structural Funds per capita transfer payments on per capita GDP in the period 2000-2006 on which our analysis is based.

Figure 1 - Geographical distribution of European regional policy intensity in the period 2000-2006. Structural Funds per capita transfer payments (percent of per capita GDP). NUTS 2006 classification.



Source: Our calculations on data of European Commission.

We consider NUTS-2 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.

Moreover, if regions are clustered into more developed areas and less developed areas, the effects of neighbors' spillovers 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. However, in presence of spatial interaction, the evaluation of European regional policy cannot be based on the Rubin Causal Model (Rubin, 1974), which explicitly excludes interference among treated and not treated units. This is the reason why in this paper we have developed an alternative method that consider spatial effects.

The **starting point** is the traditional approach to evaluate policy effect in a counterfactual framework using a continuous treatment, named "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, 2008, Cerulli, 2012; Magrini et al. 2017, Cerulli and Ventura, 2021, Cerulli et al, 2022), 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 spillover 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 population-normalised amount of funds received by each region.

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 Section 2, 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 public aid 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 NUTS-2 grid, show that Objective 1 transfers have a positive but not statistically significant impact on the regional GDP growth rate. Two papers are methodologically based on the GPS matching. **Becker et al. (2012),** 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. (2018)** investigate the 2007-2013 programming period using several outcome variables, including education and innovation outcomes, and the NUTS-2 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 (2018)** 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.

A review of the recent Italian literature on the topic of interference in counterfactual evaluation can be found in Cerqua and Pellegrini (2020).

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 exposed to similar spillover effects due to the treatment, and the difference between treated and not treated outcome identifies the "net" or "direct" treatment effects (i.e., net of spillovers). The easiest method is to incorporate the intensity of spillovers, 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. The method allows us to study the relationship between dose (funding intensity) and response (regional growth) controlling for interference between regions.

3. Relaxing SUTVA in presence of spatial dependence

Our methodological approach is easily described starting from the definition of propensity score.

Rosenbaum and Rubin (1983) show 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.

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

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, we can define a "spatial" PS (PSspat), that exploits the spatial correlation (De Castris and Pellegrini, 2015). The probability of participation is therefore conditioned to the level of spillovers:

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

This definition is based on the assumption of first-order spatial dependence between units, parametrized by a spatial first order autoregressive process, weigthed by the distance (Ord, 1975).

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 close 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.

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

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:

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

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:

(5) $$Y_i = Y_i(T_i)$$

Let r the conditional density of the treatment given the covariates X and the treatment T:

(6) $$r(T; X) = f_{T|X}(T|X)$$

The generalized propensity score is defined by *(10)*. 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 units having 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 regions:

(7) $$R_i = r(T_i; X_i; w_i X_{-i})$$

A key assumption, 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.

(8) $$Y_i(T_i) \perp T_i \mid X_i, w_i X_{-i} \quad \text{for all } t \in T$$

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:

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

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 $\beta(t,r)$ 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 $r(t,X)$:

$$(10) \qquad \mu(t) = E[E[Y(t) \mid r(t,X)]]$$

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

$$(11) \qquad E[Y|T;R] = a_0 + a_1 T_i + a_2 T_i^2 + a_3 T_i^3 + a_4 R + a_5 R^2 + a_6 R^3 + a_7 T^* R$$

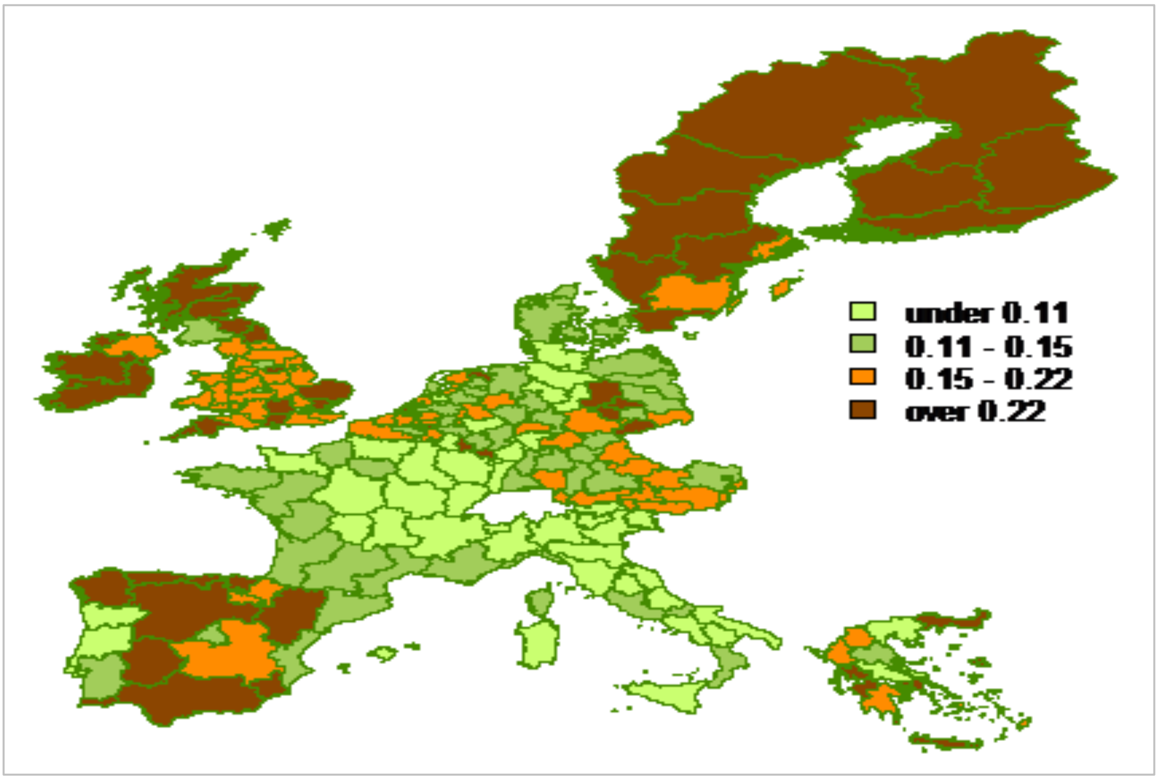
5. Data

We use an **integrated dataset**, including European data on Structural Funds and Cohesion Fund payments for the period 2000-2006 by NUTS-2 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 NUTS-2, education by level, and regional indicators on structural dimension. The treatment variable, i.e. **the dose, is defined as the payment transfers** to each region in the funding period 2000-2006, in percent of the region's population.

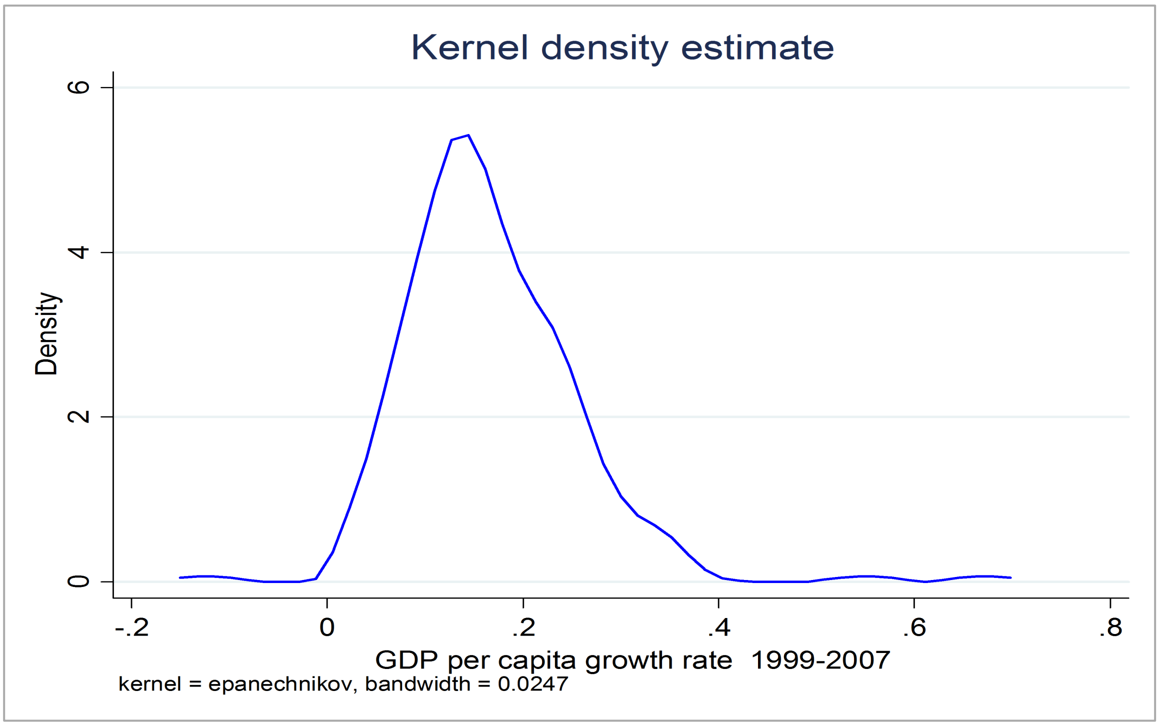
We take into account the **spatial dependence between regions**, in order to estimate a spatial generalized propensity score. We introduce a spatial weights matrix W that expresses the existence of a neighbour relation between regions as a binary relationship, with weights 1 and 0. In this way we capture the spatial interactions under consideration in our model: treatment spillovers 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.

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



Source: Our calculations on data of European Commission

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



Source: Our calculations on data of European Commission.

Table 1- 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
Outcome	
Output_UE	Gross Domestic Product per capita growth rate, period 1999-2007

6. Results

We estimate the dose-response functions using the approach developed by Bia and Mattei (2008).

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. Results of the estimation are in the table 2.

Estimating a generalized propensity score, we construct the dose response functions (Figures 4 and 5) and the corresponding marginal treated effects, in the two cases, with and without interference (table2).

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 that 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 contribution of the spillover is on average positive even if not always statistically significant.

Figure 4 – Estimates without interference

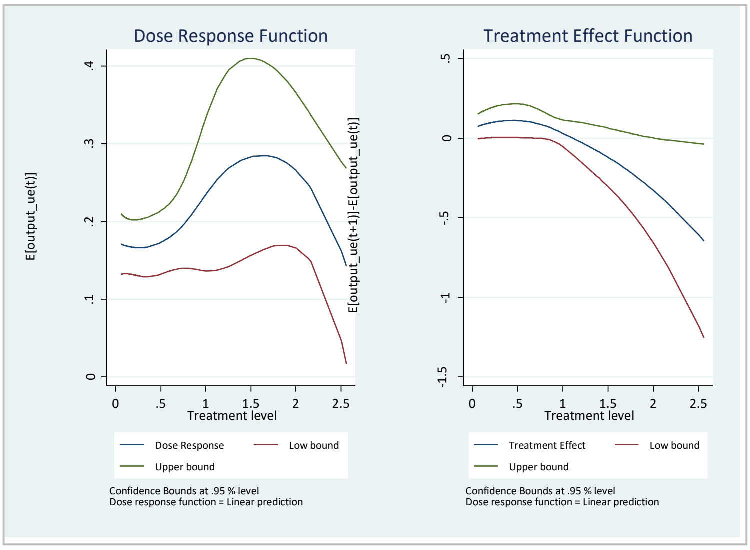


Figure 5 – Estimates with interference

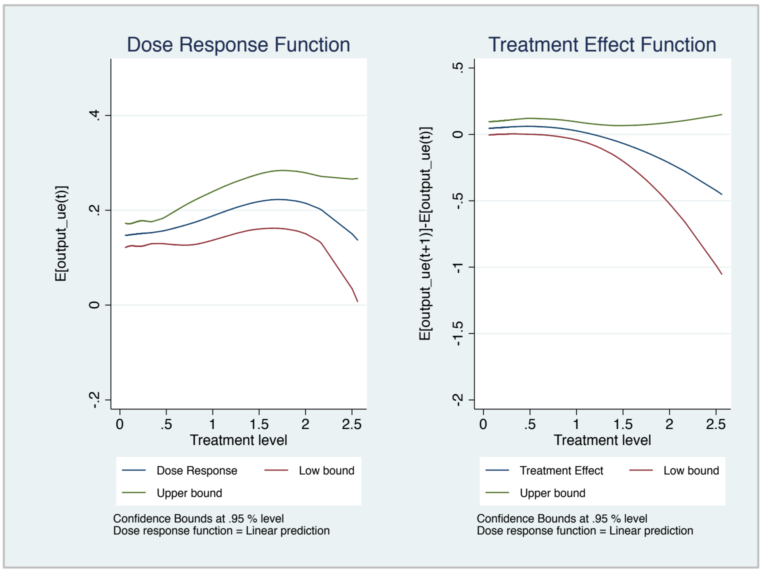


Table 2- Marginal effects of the European Regional Policy treatment. *Y is per capita GDP growth rate in 1999-2007.*

		Marginal effects without interference		Marginal effects with interference	
Treatment Percentile	**Treatment Intensity**	**dy/dT**	**Std error**	**dy/dT**	**Std error**
1st	9.5	-0.000220	0.000574	-0.000240	0.000548
5th	12.8	-0.000181	0.000543	-0.000197	0.000519
10th	14.7	-0.000159	0.000526	-0.000172	0.000503
25th	22.4	-0.000075	0.000458	-0.000077	0.000442
50th	32.1	0.000023	0.000381	0.000033	0.000370
75th	85.1	0.000411	0.000155	0.000470	0.000135
90th	208.4	0.000336	0.000249	0.000440	0.000232
95th	253.7	-0.000035	0.000240	-0.000047	0.000255

7. Neighbouring effects in Southern European Regions

In order to show the neighbor effects in European regions which 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 3- Southern European Regions in our analysis

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

Table 4- Main variables for Southern European Regions and all the Others

	Others	SER
N. regions	167	33
GDP per capita 1988	25534	14623
Population Average	1879	1821
Area Km square	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 5- Differences in the neighbours' covariates of our sample of SER

Spatial lag variables (neighbors)	Others	SER
GDP pc 1988	24940	18728
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 as treatment) and the marginal effect on output (dy/dt)

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

(13) 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 90th 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 the treatment equal to 215 euros, close to the amount of per capita yearly Structural Funds in SER (see table 4). The marginal effects are in table 2. Note that the marginal effect is statically significant around this funds intensity. The final results are in table 6: 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 6– Computation of spillover effects

Interference	Type of Marginal effect	Estimated Marginal effect (a)	Fund per capita (euro)	Effect on GDP growth rate per capita in 1999-2007
No	gross	0.0004402	215	7.2%
Yes	net	0.0003360	215	9.5%
Spillover effects	gross - net			-2.3%
Yearly Spillover effects				-0.3%

8. Conclusions

The analysis shows how the role of spatial spillover effects can shed new insights into the measure of the impact of ERP.

First of all, the results confirm 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 (2012) and Cerqua and Pellegrini (2018), with and without spatial spillovers.

Moreover, the NUTS-2 regions with lower level of funds show a larger impact of ERP on per capita GDP than the NUTS-2 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 ERP in Southern European Regions (the Objective 1 regions), the dose-response function is positive and statistically significant; the impact of ERP is positive for the average region 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 can 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 both by an excessive level of ERP for some (few) regions and by the presence of negative spillover effects between contiguous low-income regions.**

References

Accetturo, A., De Blasio, G., & Ricci, L. (2014). A tale of an unwanted outcome: Transfers and local endowments of trust and cooperation. *Journal of Economic Behavior & Organization*, 102, 74-89.

Arpino, B., and Mattei, A. (2016). Assessing the causal effects of financial aids to firms in Tuscany allowing for interference, *The Annals of Applied Statistics*, 10 (3): 1170-1194.

Bachtrögler, J., Fratesi, U., & Perucca, G. (2020). The influence of the local context on the implementation and impact of EU Cohesion Policy. *Regional Studies*, 54(1), 21-34.

Becker S.O., Egger P.H., and von Ehrlich M. (2012). "Too much of a good thing? On the growth effects of the EU's regional policy", *European Economic Review*, 56 (4): 648-668.

Becker S.O., Egger P.H., and von Ehrlich M. (2016). "EU Regional Policy" in: Harald Badinger and Volker Nitsch (eds.). Handbook of the Economics of European Integration, Chapter 17, Routledge.

Becker S.O., Egger P.H., and von Ehrlich M. (2018). Effects of EU regional policy: 1989-2013, CAGE Online Working Paper Series No. 271. *Regional Science and Urban Economics*, 69, 143-152.

Bia M. and Mattei A. (2008). A Stata package for the estimation of the dose–response function through adjustment for the generalized propensity score, *The STATA Journal*, 8 (3): 354-373.

Bouayad-Agha S., Turpinn N. and Védrine L. (2011). "Fostering the development of European regions: a spatial dynamic panel data analysis of the impact of cohesion policy", *Regional Studies* 47, 1573–1593.

Breidenbach P., Mitze, T. and Schmidt C. M. (2016). EU structural funds and regional income convergence: A sobering experience, Ruhr Economic Papers, No. 608, ISBN 978-3-86788-705-2, http://dx.doi.org/10.4419/ 86788705

Cerqua, A. and Pellegrini, G. (2017). "Industrial policy evaluation in the presence of spillovers", *Small Business Economics*, 49 (3): 671–686.

Cerqua, A. and Pellegrini, G. (2018). "Are we spending too much to grow? The case of Structural Funds", *Journal of Regional Science*, 58, 535–563.

Cerqua, A., & Pellegrini, G. (2020). Evaluation of the effectiveness of firm subsidies in lagging-behind areas: the Italian job. *Scienze Regionali*, 19(3), 477-500.

Cerulli, G. (2012). A continuous treatment model for estimating a Dose Response Function under endogeneity and heterogeneous response to observable confounders: Description and implementation via the Stata module "ctreat", CERIS Working Paper N°18/2012.

Cerulli, G. (2015). Identification and estimation of treatment effects in the presence of (correlated) neighborhood interactions: Model and Stata implementation via ntreatreg. *The Stata Journal*, 17 (4): 803-833.

Cerulli, G., & Ventura, M. (2021). A dose–response approach to evaluate the effects of different levels of partial credit guarantees. Applied Economics, 53(12), 1418-1434.

Cerulli, G., Corsino, M., Gabriele, R., & Giunta, A. (2022). A dose–response evaluation of a regional R&D subsidies policy. *Economics of Innovation and New Technology*, 31(3), 173-190.

Crescenzi, R., & Giua, M. (2020). One or many Cohesion Policies of the European Union? On the differential economic impacts of Cohesion Policy across member states. *Regional Studies*, 54(1), 10-20.

Dall'erba, S. and Le Gallo, J. (2008). "Regional convergence and the impact of European Structural Funds over 1989–1999: a spatial econometric analysis", *Papers in Regional Science* 87, 219–244.

Dall'erba, S. and Fang, F. (2017). "Meta-analysis of the impact of European Union Structural Funds on regional growth", *Regional Studies*, 51(6): 822-832.

De Castris, M. and Pellegrini, G. (2015). Neighborhood effects on the propensity score matching. Università degli Studi Roma Tre, CREI Working Papers, n.5/2015, 1-24.

De Castris, M., & Pellegrini, G. (2019). Spatial Evaluation of Public Credit Guarantees for Italian SMEs. *Scienze Regionali*, 18(2), 291-306.

Di Caro, P., & Fratesi, U. (2022). One policy, different effects: Estimating the region specific impacts of EU cohesion policy. *Journal of Regional Science*, 62(1), 307-330.

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. Spatial economic analysis, 5(1), 9-28.

Fiaschi, D., Lavezzi, A. and Parenti, A. (2018), "Does EU Cohesion Policy Work? Theory and Evidence", *Journal of Regional Science*, 58 (2): 386-423.

Gagliardi, L., & Percoco, M. (2017). The impact of European Cohesion Policy in urban and rural regions. *Regional Studies*, 51(6), 857-868.

Holland, P. (1986). "Statistics and causal inference". *Journal of the American Statistical Association*, 81 (396): 945–960.

LeSage J. and Fischer M. (2008). "Spatial Growth Regressions: Model Specification, Estimation and Interpretation", *Spatial Economic Analysis*, 2008, 3 (3): 275-304.

LeSage, J. and Pace, R. K. (2009). Introduction to Spatial Econometrics. CRC Press.

Magrini E, Montalbano P. and Nenci S. (2017). "Are EU trade preferences really effective? An impact evaluation assessment of the Southern Mediterranean Countries' case", *International Review of Applied Economics*, 31(1): 126-144.

Mohl P. (2016) Empirical evidence on the macroeconomic effects of EU cohesion policy, Wiesbaden: Springer Gabler.

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

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

Pieńkowski J. and Berkowitz P. (2015) Econometric assessments of Cohesion Policy growth effects: How to make them more relevant for policy makers? Regional Working Paper 2015, European Commission, WP 02/2015, 1-16.

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