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Neighborhood Effects on the Propensity Score Matching

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Abstract: The focus of our paper is the identification of the regional effects of industrial subsidies when the presence of subsidized firms is spatially correlated. In this case the stable unit treatment value assumption (SUTVA) in the Rubin model is not valid and some econometric methods should be used in order to detect the consistent policy impact in presence of spatial dependence. We propose a new methodology for estimating the unbiased “net” effect of the subsidy, based on novel “spatial propensity score matching” technique that compare treated and not treated units affected by similar spillover effects due to treatment. We offer different econometrical approaches, where the “spatial” propensity score is estimated by standard or spatial probit models. Some robustness tests are also implemented, using different instrumental variable spatial models applied to a probit model. We test the model using an empirical application, based on a dataset that incorporates information on incentives to private capital accumulation by Law 488/92, mainly devoted to SME, and Planning Contracts, created for large projects, in Italy. The analysis is carried out on a disaggregated territorial level, using the grid of the local labour system. The results show a direct effect of subsidies on subsidized firms. The sign of the impact is generally positive, the output effect outweighing the substitution effect. Confronting the standard and the “spatial” estimation, we observed a positive but small crowding out effect across firms in the same area and across neighbouring areas, mostly in the labour market. However, due to the small sample, the difference in impacts estimated by the standard and the “spatial” effect of subsidies is not statistically significant.

Keywords: spatial propensity score, policy evaluation, propensity score matching, spatial analysis

JEL classification: R12, R23, C21.

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1. Introduction

Nowadays, the analysis of spatial effects of industrial subsidies is attracting the interest of more scholars from the field of policy evaluation. However, the literature on the quantitative evaluation of spatial effects of industrial incentives is rather rare: in fact, very few papers analyse the effect of the spatial diffusion of industrial policies based on subsidies to private firms (De Castris and Pellegrini, 2005, 2012; Bondonio and Greenbaum, 2006; Cerqua and Pellegrini, 2013).

Among others, there are important empirical and theoretical reasons: empirically, the lack of reliable and comparable information at territorial level using a narrow spatial grid prevents to clearly define the spatial effect of regional policies; theoretically, it is not easy to frame the spatial analysis of industrial subsidies in the context of the modern literature on causal effects based on the Rubin Causal Model (Rubin, 1974), that explicitly exclude interference among treated and not treated units.

The presence of a spatial interaction implies that subsidy in a region also affects also contiguous regions. In this case the stable unit treatment value assumption (SUTVA) in the Rubin model is not valid and some econometric methods should be used in order to detect the consistent policy impact in presence of spatial dependence. Usually, traditional industrial policy analyses explicitly face selection bias issues but do not control for spillover effects. These analyses correctly identify the counterfactual sample among unsubsidized firms located on the eligible territory with the most similar features in respect to the subsidized firms; nevertheless, in presence of spillovers even a perfect control of the selection bias will not be enough to avoid a biased estimate of the program effect (Cerqua and Pellegrini, 2013). Indeed, only if we incorporate knowledge about how spillovers spread, we can use these unsubsidized firms as a correct control group.

Actually, this is the evaluation strategy we adopted in the paper. We propose a novel “spatial propensity score matching” technique that allow to correct for the spatial bias. The idea is that if we compare treated and not treated units subject to similar spillover effects due to treatment, we can identify the “net” or “direct” treatment effects (i.e. net of spillover). The easiest way is to estimate the spatial dependence across areas and incorporate it in the propensity score (PS) estimation. There are several techniques for incorporating the information about spatial spillovers in the PS. In the paper we discuss several approaches and compare the different results. However, our approach has a cost: we cannot estimate simultaneously and consistently the spillover effects, but we can only
derive them indirectly by comparing the results obtained with the standard approach with those resulting from our method.

The new estimator is applied on a dataset that incorporates information on the two more important measures for local development in Italy: incentives to private capital accumulation by Law 488/92, mainly devoted to SME, and Planning Contracts (contratti di programma), created for large projects (see De Castris and Pellegrini, 2005). The dataset considers structural and geographical information from administrative data bank on regional policies and statistical database. The analysis is carried out on highly disaggregated territorial level, using the grid of the local labour system (LLS) in Italy. Using data for 473 local labour systems concerning the South of Italy and three regions in the North (regions in which the two instruments have a reasonable influence), we estimate the employment effect of subsidies, controlling for the presence of spatial effects, specifying an appropriate spatial model.

Only some papers evaluate policy effects of industrial incentives taking into account spatial spillovers. Both Bondonio and Greenbaum (2006) and De Castris and Pellegrini (2012) try to quantitatively estimate the spillover effects at the macro level, making use of local areas as units. Using a regression approach, De Castris and Pellegrini (2012) find a modest spatial crowding out, whereby subsidised regions attract employment and investments from neighbouring areas. Cerqua and Pellegrini (2013) evaluate the micro effects of investment subsidies policies using firms as units. Adopting a Matching difference-in-differences (DID) approach, they find positive spillovers in terms of investments and negative spillovers in terms of employment, but these estimates are statistically insignificant. A new approach, using a spatial DID, is in Delgado and Florax (2015).

The information relating to specific characteristics of the neighbours, specifically respect to their number and the share of the treaties, can be easily incorporated into the PS. On the other hand, it does not appear exhaustive since the intensity of spillovers can result from a number of features, which in our case are mainly related to the probability of being treated. An easy way to incorporate these features in our estimates is to synthesize them in the PS. This means introducing in estimating PS also the PS of the neighbours. Technically, this refers to introducing a spatial lag in the estimation of PS, and then get a "spatial" PS estimates.

We are aware of only one other paper using a spatially conditioned propensity score matching estimation, that is Chagas and al. (2012). They estimate the effect of growing sugarcane on the
human development index (HDI) in cane producing regions. Location effects are controlled by spatial econometric techniques, giving rise to the spatial propensity score matching model. However, in the paper they use the spatial model only for cleaning the residuals from spatial effects.

In our paper we have different approaches, concerned with the presence of spillover effect generated by the subsidies among neighbours. A simple approach is based on the introduction of some information on the number or the share of treated neighbours. A more complex approach is based on the introduction of the spatial lagged dependent variable in the propensity score equation because we believe that there is a strong spatial dependence across subsidies areas, and the factors affecting the probability to be subsidized are important to determine the presence and the size of spillover effects. Empirically, we assume that the matching is correct only if the treated and not treated LLS have the same number or share of treated neighbours or neighbours with the same probability to be subsidized. This assumption implies that that crowding out effect across neighbouring LLS are equal. Therefore our new method allows detecting the direct effect of the program on subsidized LLS, netting out the indirect effects.

The paper is structured as follows. Section 2 briefly describes the methodology we adopt for the identification of the net effect of the policy when firms are spatially correlated. The proposed econometric models are presented in Section 3, followed by a description of the institutional design of the policy instruments (L. 488 and Contratti di Programma) evaluated in the empirical application in Section 4. The database related to the two policy instruments is discussed in Section 5. The results of the empirical analysis are presented in Section 6. Section 7 concludes and defines some paths for future research.

2. A methodology for relaxing the SUTVA in policy evaluation

Let us consider a framework where there are firms, regions or local areas (i.e. the set of firms inside a region or a local area) that are subsidized and there are spillovers across firms, regions or areas. If we apply Rubin’s (1978) causal model in a conventional way, we will define the effect of a public subsidy on subsidised firm (or region) as the difference between the outcome the firm (or the region) would display if subsidized (treated) and the outcome if not subsidized (not treated). This firm-specific (or region-specific) effect is defined under the stable-unit-treatment-value assumption (SUTVA) that there is a single value of each potential outcome associated with each treatment for
each experimental unit, regardless of how the treatments are assigned and what treatments are received by other experimental units (Rubin 1986). However, most researchers simply invoke SUTVA without further theoretical or empirical scrutiny. As Rubin (1990) cautioned, SUTVA becomes problematic in several situations: for example, when subsidies are given to firms (or regions) that spatially interact with one another. Actually, the traditional evaluation analysis identifies the unsubsidized firms (regions) located in the vicinity of the subsidized firms as those firms (regions) with the features most similar to those of the treatment group. This approach is based on the SUTVA hypothesis, that is absence of spillover effects. However, in the presence of spillovers, even a perfect control of selection bias will not suffice to prevent biased ATT estimates (Cerqua and Pellegrini, 2013). Indeed, if some control units undergo policy spillovers, they will not be suitable for the control group unless perfect knowledge about how spillovers spread is assumed and dealt with. For instance, in case of negative spillover effects on unsubsidized firms (regions) located in the vicinity of one or more subsidized firms (regions) that belong to the same sector of activity, traditional analyses will deliver an overestimate of the ATT even when selection bias is completely absent.

Consider a group of firms indexed by \( i = 1, \ldots, N \). Let the random variable \( D_i \) denote a treatment indicator which is equal to 1 if treatment is received by firm and 0 otherwise. Let \( D = (D_1, \ldots, D_i, \ldots, D_N) \) represent the treatment assignment for all firms. Following Hong and Raudenbush (2013), we describe the potential outcome for firm \( i \) as a function of the firm’s own treatment assignment \((D_i)\), the treatment assignment of other firms \((D_{-i})\), as well as the assignment of the focal firm to a different intensity of treatment \((j)\). For firm \( i \) with intensity of the treatment \( j \), the potential outcome is denoted by \( Y_i(D, j) \).

In this framework the potential output of each firm is affected by the potential output of all firms and by all the different intensities of treatment. The SUTVA is a special case where \( Y_i(D, j) = Y_i(D_i) \). In words, the SUTVA states that the treatment assignments of firms other than \( i \) and the intensity of the treatment received by firm \( i \) have no effect on firm \( i \)'s potential outcomes. However, SUTVA implies a strong simplification of our problem, and sweep out the possibility of spillover across firms. Our opinion is that a more realistic reduction in the complexity of the causal inference framework is needed in order to achieve a more convincing solution. We use two simplifying assumptions:

**Assumption 1:** There is only 1 version of the treatment (1st part of the SUTVA), i.e.,

\[
j = \text{constant}, \quad \forall i;
\]

---

1 The objects of the following analysis are the subsidized/non subsidized firms, but the analysis can be applied to regions without changes.
Assumption 2: There is spatial dependence across firms. We impose structure on the spatial dependence relations allowing the dependence relation to have specific parameters. We adopt the parsimonious parameterization for the dependence relations proposed by Ord (1975), named spatial first-order autoregressive process. Applied to our problem, we have:

\[(1) \quad Y_i(D) = Y_i(D, w_iY_{-i}(D))\]

Where \(w_i\) is the row \(i\) of the usual spatial weight matrix \(W\) (based, for instance, on the first-order contiguity relations across firms). The cross-product \(w_iY_{-i}\) is called a spatial lag, since it represents a linear combination of values of the variable \(y\) constructed from observations/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:

**Definition 1.** The treatment effect for the subsidised firm \(r\):

\[(2) \quad Y_r(D_r = 1, w_rY_{-r}(D_{-r})) - Y_r(D_r = 0, w_rY_{-r}(D_{-r}))\]

Because of the fundamental problem of causal inference, we estimate the average effect:

**Definition 2.** The ATT:

\[(3) \quad E[Y_i(D_i = 1, w_iY_{-i}(D_{-i})) - Y_i(D_i = 0, w_iY_{-i}(D_{-i}))|D]\]

The counterfactual scenario for the ATT consists in changing the assignment for firm \(i\) from \(D_i = 1\) to \(D_i = 0\) without removing the subsidy to all the other firms in the neighbours of \(i\). Those assumptions will allow us to partially relax the SUTVA. This is not the only possible choice: in the counterfactual scenario Cerqua and Pellegrini (2013) remove also the subsidy to all the other firms in the neighbours of \(i\), i.e., \(D_{-i}\) is changed to the null vector if \(D_{-i} \neq 0\). Our approach allows a easier identification and estimation of the ATT, because it can be used most of the sample of not subsidized firms as control group. However, differently from us, the approach used by Cerqua and Pellegrini (2013) allows also the identification of spillover effects, even if the assumptions they considered are fairly strong.

3. The empirical approach

The evaluation problem in the paper is to measure the impact of industrial policy program on an outcome variable (Y) for each territory (LLS), using the ATT estimator described in the previous paragraph.
In our framework, the analysis is carried out using a nonparametric approach, such as 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 on observable, that is, it can be taken into account by conditioning on observed LLS characteristics.

The matching estimator (MM) is given by:

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

(4)

where \( Y_i^S \) and \( Y_j^{NS} \) are the post-program outcomes for subsidized and non-subsidized LLSs, respectively; \( \omega_{ij} \) is a weight indicator of the similarity between the two LLSs before the subsidy was provided; \( \omega_i \) accounts for the re-weighting that reconstructs the outcome distribution for the subsidised sample.

The main advantage offered by the matching method is that it does not require any assumption about the functional form of the dependency between the outcome variable and the observed covariates. On the other hand, if the covariates are numerous, it may be difficult to identify non-subsidized LLS to match with every subsidized LLS, unless the sample is huge.

Empirically, as the number of characteristics used in the match increases, the chances of finding a match reduce. This obstacle is overcome thanks to an important result (Rosenbaum and Rubin, 1983) which shows that matching on a single index reflecting the probability of participation may achieve consistent estimates of the treatment effect in the same way as matching on all covariates.

This index is the PS and this variant of matching is well-known as “propensity score matching”. Any standard probability model can be used to estimate the PS, such as for example

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

(5)

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

The estimation of a standard propensity score in our empirical application shows that the residual
are spatially correlated. One of the main reasons is the presence of spatial spillovers. If incentives are effective in generating spatial externalities and spatial spillovers, they should be empirically measured by the presence of a positive spatial correlation in some outcome variables (like regional value added, production, and employment) (De Castris and Pellegrini, 2012). Moreover, the localization of the subsidized firms could follow a positive spatial correlation pattern. Nevertheless, the subsidized firms could replace firms and investments project in the neighbouring areas, by a spatial crowding out effect in the input, output and in the labour markets. These effects could decrease the spatial positive correlation. The net effect on spatial correlation is therefore undetermined. In both cases the probability of firm or region (LLS) to be treated (for instance, to have a substantial share of investments that is subsidized) depends on the probability that the contiguous firms or regions (LLS) are treated.

In this framework, the use of the SUTVA hypothesis is clearly wrong. We can apply the methodology previously described to the selection of the correct counterfactual scenario, that is, the correct propensity score. A natural approach is to match treated and not treated firms with the same number of share of treated neighbours. From a econometric point of view, the solution is the introduction of a “spatial” variable related to the number (PSa) of share (PSb) of treated neighbours for each firms, and this is the first technique used in the estimation.

However, this approach does not solve two major problems: it does not exploit the presence of spatial correlation in the determination of the PS and does not take into account the fact that some factors that explain the PS are also driving forces behind spillover. For example, a positive effect on the PS is exerted by the size of the companies, or by membership in the manufacturing sector, or being in an urban area, all of which positively affect the presence of spillover. These considerations suggest to add the spatial lag of the PS in the estimation of the PS. From an econometric point of view, the problem can be deal with estimating an appropriate spatial lag model (Anselin, 1988) having as dependent variable the spatial propensity score ($PS_{spat}$).

Let be $PS_{spat}$ a N by 1 vector, we define:

\[ (6) \quad \text{SLagPS} = W^* PS \]

that is the first-order spatial lag of the PS, and we can use it in the estimation of the spatial PS:
\( P_{Spat} = F(h(X), g(SLagPS)) \)

where:

- \( X \) is a matrix of \( N \) observations by \( k \) covariates
- \( W \) is the \( N \times N \) spatial weight matrix based on the binary contiguity of LLS.

The definition of the matrix \( W \) is based on the contiguity of LLS: each element of the matrix \( W_{ij} \) is equal to 1 when \( i \) and \( j \) are two LLS contiguous, and 0 otherwise. We assume that two LLS are contiguous if the distance among their centroids is lower than 53 kilometres. This cut-off has been determined in order to maximise the level of spatial autocorrelation (the absolute value of significant Moran’s I) of the main policy variable (basically, the new employment created by the subsidized investments). The distance is greater than the minimal allowable cut-off, i.e. the cut-off for which each unit has at least one neighbour (39 kilometres). The procedure guarantees that the higher level of spatial connection related to the subsidies is considered, following a well-tested approach of Baumont, Ertur and Le Gallo (2001). Moreover, we assume that interactions among regions more distant than 53 kilometres are negligible. The elements, of the spatial weights matrix \( W \), are row-standardized, such that for each row, the sum of the elements is equal to one.

In this context equation 7 defines a “spatial” propensity score for each unit of observation, taking into account not only the \( k \) covariates that characterized the LLS but also a vector which contain the value of \( PS \) for the contiguous LLS and 0 otherwise. We can apply the matching procedure using the spatial \( PS \) instead of the standard propensity score.

Given equation 7, the empirical estimation of the spatial \( PS \) requires a spatial autoregressive probit model (PS-SAR):

\[
PS_{spat} = \rho SLagPS + X\beta + \epsilon \sim MVN(0, \sigma^2 \epsilon*I) \\
D = I(PS_{spat} > 0.5)
\]

where \( SLagPS \) is defined in eq. 6, \( \rho \) is the spatial autoregressive coefficient \( X \) is a matrix of covariates including the constant term, \( \beta \) is the corresponding vector, including intercept, \( \epsilon \) is a vector of \( iid \) normal error terms, and \( D \) is the observed binary vector equal to 1 in presence of treatment. \( D \) is a indicator-function of the unobserved continuous variable \( PS_{spat} \), and the model describes the probability that the \( ith \) observation is treated.
Under the previous hypothesis, we move from the structural form (eq. 8) to the reduced form:

\[PS_{spat} = (I - \rho W)^{-1}(X \beta + \epsilon) = (I - \rho W)^{-1}X \beta + u\]

and the \(P_{sspat}\) can be estimated by the spatial probit model:

\[P(Y=1|X, SLagP) = \Phi(X\beta)\]

where \(\Phi\) is the cumulative density function for the normal distribution.

The empirical specification of the spatial propensity score is not trivial. The ML estimation uses the reduced form (eq. 9) but has to deal with the heteroskedasticity generated by spatial dependence. Several estimators are proposed (see Billè, 2013 and Arbia and Billè, 2013). In the paper we use a bayesian spatial discrete choice model (SAR-PS), estimated by the Gibb sampler, following Wilhelm and de Matos (2013).

However, as a robustness analysis, we compare our results with three different estimators. Given the presence of the contemporaneous spatial lag of PS, a simple probit or logit model cannot estimate correctly the coefficient of \(P_{Sspat}\), because the error term is correlated with the other variables and the estimates are biased.

An unbiased estimator requires instrumenting the variable \(SLagPS\), that is the probability to have a subsidized neighbour. Therefore we need an instrumental variables estimator where both the dependent variable and the endogenous explanatory variable are generated by a non-linear model.

\(^2\)There is not a simple solution, and this is the reason why we present three different methods for estimating the spatial propensity score, that are compared with the spatial probit estimated by Bayesian approach.

The first method uses the ML approach \((P_{Sspat})\): a maximum likelihood estimator of a binary outcome with endogenous binary regressor can be implemented, as long as a model for the endogenous explanatory variables can be fully specified, along with the fully parameterized joint

\(^2\) In this case we cannot use a 2SLS estimator: this is a very well-know problem, sometimes called the “forbidden regression” (Angrist and Pischke, 2009, p. 190), and in general the relationship of interest cannot be consistently estimated using 2SLS. The problem is that neither the conditional expectations operator nor the linear projection remains valid under nonlinear functions. For this reason only an OLS regression in the first stage is guaranteed to produce fitted values that are uncorrelated with the residuals.
distribution of the error terms in the two models. However, the ML estimator requires to parameterize everything and is generally not very robust to misspecifications of both the models and of the endogenous variables.

A more robust method is the use of the LPM (linear probability model) in the first stage and the probit model in the second stage ($PS_{spat2}$). The obvious flaw in the LPM is that its fitted values are not constrained to lie in the unit interval, so that predicted probabilities below zero or above one are commonly encountered. However, a common rejoinder to these critiques is that the LPM is only intended to approximate the true probability for a limited range of X values. For instance, Jeffrey Wooldridge’s widely used undergraduate text, Introductory Econometrics: A Modern Approach states: “Even with these problems (computation of the predicted probability and marginal effects), the linear probability model is useful and often applied in economics. It usually works well for values of the independent variables that are near the averages in the sample.” (2009, p. 249).³

The third method is based on the approach presented in Adams et al. (2009) ($PS_{spat3}$). They use a three-step procedure, where they have a probit "first stage" and an OLS second stage without falling for the forbidden regression problem. Their general approach uses probit to regress the endogenous variable on the instruments and exogenous variables, uses the predicted values from the previous step in an OLS first stage together with the exogenous (but without the instrumental) variables, and finally estimates the second stage as usual. In our approach the second stage is a probit model.

The estimated $PS_{spat}$ are usually very close each other. Given a correct estimate of $PS$ and $PS_{spat}$, they can be used in a matching approach for the estimation of the effects of program on the outcome. We implemented the matching algorithm in order to identify the average treatment effect on treated (ATT). ATT is estimated using a DID Matching estimator (MDID) that can provide better performance than traditional matching estimators (Blundell and Costa Dias, 2008). The DID Matching is implemented by a Kernel matching estimator, that maximizes the set of LLS used in the analysis, using the Radius matching estimator as a robustness check. The standard errors of the ATT are estimated by the bootstrap procedure (1000 replications) described in Becker and Ichino (2002).

The standard propensity score is estimated using as covariates: unemployment rate (1996), share of agricultural employment (1996), value added growth rate in service sector (1996-2001), , dummy

³ It is implemented using the Stata command ivprobit.
for southern regions, dummy for urban LLS. The estimated model is statistically significant (the pseudo R-square of the equation is 0.11) and the balancing property is satisfied. However, there is a clear spatial autocorrelation of the estimated propensity score: the Moran Index I is equal to 0.703, the z value is more than 46. The result reflects the spatial correlation of incentives (Moran Index I equal to 0.197, strongly significant).

Using the previously described methods we have estimated the spatial propensity score, using the two described approaches: the insertion of “spatial variables” in the standard approach and the insertion of a spatial lag of the propensity score as endogenous explicative variable. In this case we include in the “second stage” probit model also the spatial lag of the covariates (excluding the growth rate of service sector). The spatial lag of the propensity score has been instrumented, using as instrument the exogenous covariates. The estimated “first stage” model is statistically significant, and the adjusted R-squared is 0.49 (in the LPM). Therefore the spatially lagged variables improve strongly our estimation.

The estimated propensity scores are used in order to detect the average effect of subsidies on labour market, on economic performance, and manufacturing specific effects.

4. Incentive schemes

We evaluate the two major place-based policies operating in Italy in the period 1996-2001, that were Planning Contracts (Contratti di Programma) and the Law 488/1992. The main goal of these instruments is to sustain the accumulation of private capital of firms located in lagged areas and to increase employment. They operate in the same regions over the same period but they had different rules to assign incentives.

Planning Contracts were introduced in 1986 and they presented a new way to identify investment project and territorial location for the investments. They promote an agreement between Central Administration and the private firms through a negotiation process. The instrument was addressed to large firms, industrial groups and SME consortia in order to promote large investment projects whose plans were negotiated with Public Administration. The instrument was oriented to the attraction of domestic and international projects favouring competition between areas and countries.
Moreover the public administrations negotiated with subsidized firms the investment's characteristics taking into account social-economic effects at national and local level.

The operation of Planning Contracts met different problems mainly for the absence of suitable administrative procedures. The more serious problem is the long waiting time to get authorization for the project. And also when the firm was authorized to realize the investment, the delivery of financial resource was slowed by involvement of political Institution, especially when the instrument was moving first steps, in the years from 1986 to 1992.

On the other hand, the Law 488/92 was a faster policy instrument addressed to medium-small and small projects. The allocation of financial resources utilized a “rationing” system based on an auction mechanism which guarantees compatibility of demand and supply of incentives.

The selection of projects that could be subsidized is the result of a procedure that compute a score on the basis of three policy indicators: 1) the share of private capital invested in the plan; 2) the number of new employees per unit of investment; 3) the ratio between demanded subsidy and the maximum subsidy which can be allocated following EU Commission rules. Each indicator is standardized and normalized before adding up the three values by project to obtain the final score. The scores are sorted by a descending order so that the subsidies can be granted to projects until the available regional funds are exhausted. These rankings are built at the regional level. There are also special rankings for large projects and reserved lists for small and medium-sized firms. The amount of requested aids by each firm (with respect to threshold established by the European Union) influences the probability of obtaining the grant: the lower the demand the higher the likelihood of receiving it. The mechanism allows firms to influence the probability of obtaining the grant and the State to reduce the granted subsidy of the firm. By ranking and selecting projects and subsidies, the government can stimulate projects with different earning capacities in different ways and maximize the number of subsidised investments given the available resources (Bernini, Pellegrini, 2011).

On the whole, the two instruments have distributed the 37.4% of the overall national subsidies to firms in the period 1998-2001 (37.2% in the period 2000-2001). However, only few programs have regional development as main target. There are several programs dedicated to internationalization, export support, aids to R&D, start-ups, environment and so on, which are not mutually exclusive or antagonist to Law 488/92 and Planning Contracts. If we consider only programs dedicated to regional development, the share in terms of total disbursement of Law 488/92 and Planning
Contracts is much larger (66.1% in the years 2000-2001). We consider here only the overall disbursement on subsidies (the total amount of money effectively received by the firms) by national programs. In the same periods different regional programs operate in the Mezzogiorno. However, the regional programs operating in the South of Italy have disbursed only around the 3% of the total disbursements (by national and regional programmes) in the same regions. Therefore the effects of regional subsidies on Southern regions are expected to be negligible with respect to the national ones.

Programs aiming to support regional growth are concentrated in the Mezzogiorno, where they distributed the 86% of the subsidies. Unfortunately, data on disbursements by years, regions and programs are not available. Using as a proxy the distribution of assigned subsidies by area, we estimate that in the period 2000-2001 the 92% of the subsidies by Law 488/92 and Planning Contracts are allocated in the Mezzogiorno. Consequently, these two programs have distributed the 70.7% of the whole subsidies dedicated to regional development in the Southern regions of Italy. Therefore, the analysis based on the subsidies distributed by Law 488/92 and Planning Contracts can capture the most important aspects of the whole spatial distribution of capital subsidies in the Mezzogiorno.

5. Data

The analysis focus on Local Labour Systems (LLSs) of the southern regions of Italy where two major instruments, the Planning Contracts and the Law 488/92, have subsidized many firms. This analysis is going to assess the effects of capital subsidies on regional employment, unemployment and productivity performance in Southern Local Labour Systems (LLSs) and some LLSs in central and northern regions, over the years 1996-2001. Empirical studies on regional effects of public subsidies usually adopt administrative territorial units, such as Nuts-2 and Nuts-3 regions, otherwise in this work we adopt the grid of local labour system. This territorial unit is a functional territorial unit able to overcome some statistical problems of areas based on administrative boundaries. A LLS is the aggregation of neighbouring municipalities where commuting flows are self-contained in it so that people live and work in the same area. In the analysis we include all the LLSs of the southern and a group of LLSs of the central and northern regions (Piedmont, Marche and Umbria) where firms cannot apply for Planning Contracts. The choice is justified by the necessity to identify a
counterfactual area for the Law 488/92. Our territorial grid is composed by 473 LLSs, of which 365 localized in the South.

Information on Law 488 has been collected through administrative archive of the Ministry for Industry. This archive records firms that have applied for the incentives, both financed and non-financed firms. The group of treated firms is identified by all the “winning projects” according to the rankings of all regional auctions (the regions of our set), which have really concluded the project in the year 2000. The instrument Law 488 is spread among firms, in fact 408 over 473 LLSs (86%) have subsidized firms in its area.

Information on Planning Contracts has been collected through administrative archive of CIPE (Inter Ministerial Committee for Economic Planning) deliberations. The analysis considers Planning Contracts realized before year 2000, so it refers to the first stage of the life cycle of this instrument. The instrument devoted to large projects is presented in a few areas, we find only 32 LLSs over 473 (7%) in which are localized treated firms.

The empirical analysis is based not only on administrative data but use economic statistics. First, we use dataset of Italian National Institute of Statistics (Istat), both survey data and census data. We get different Istat’s sources to define outcome variables and covariates: time series of domestic employment and value-added in agriculture, industry and services sectors by LLS, for the years 1996-2002 by Istat estimates; comparable data on plant employees in agriculture, industry and services sectors, years 1991, 1996, 2001 by LLS from Industry and Service Census; population of the year 2001, from 14th Census of Population; resident employment and unemployed persons for the years 1998-2002, by LLS; estimates of resident employment and unemployed persons, year 1996, by LLS.

In the analysis we also consider a set of covariates related to the socio-economic structure of the LLS before the treatment:

- Unemployment rate by LLS in the year 1996 (tasdis96)
- Agriculture employment - Share by LLS in the year 1996 (qocc_agr96)
- Value added growth rate of services in the period 1996-2001 (tva_ser9601)
- Plant employees growth rate in the period 1996-2001 (tasadd9196)
- Dummy for subsidized LLS (du_subsidy5)
- Dummy for LLS characterized by urban area with more than 300,000 (thousand) inhabitants (urbani)
- Dummy for LLS localized in the Southern regions (mez)

Moreover, we take into account the spatial effects of neighboring LLS considering a set of spatial lagged variables:

- Spatially lagged unemployment rate by LLS in the year 1996 (lagtasdis96)
- Spatially lagged share of agriculture employment by LLS in the year 1996 (lagqoccagr96)
- Spatially lagged value added growth rate of services in the period 1996-2001 (lagtva_ser9601)
- Spatially lagged plant employees growth rate in the period 1996-2001 (lagtasadd9196)

The analysis is based on the local labour systems (LLSs). We should define a LLS as a treated unit if it contains any of the firms that have been subsidized. As previously described, the policy program has subsidized basically all LLS: actually, subsidized firms are localized in almost all the considered LLS. However, it is reasonable that the effects of the intervention are substantial (and can be detected by an econometric model) only when it represents a significant share of the investment realized in the LLS. So we consider that a LLS is treated (subsidized) if the share of subsidized investment is larger than 5%. However, our dataset contains only employment (and not total investment). Therefore LLS is treated if the share of subsidized new employment is larger than the 5% on the total new employment in manufacturing.

Distribution of LLS by treatment and characteristics

<table>
<thead>
<tr>
<th></th>
<th>Treated</th>
<th>Not treated</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>190</td>
<td>283</td>
<td>473</td>
</tr>
<tr>
<td>Urban LLS</td>
<td>6</td>
<td>19</td>
<td>25</td>
</tr>
<tr>
<td>Not urban</td>
<td>184</td>
<td>270</td>
<td>454</td>
</tr>
<tr>
<td>Southern LLS</td>
<td>178</td>
<td>187</td>
<td>365</td>
</tr>
<tr>
<td>Central LLS</td>
<td>12</td>
<td>96</td>
<td>108</td>
</tr>
</tbody>
</table>
6. Results

The results for the estimation of the various ATT, using the standard propensity score \( PS \) and the spatial propensity score \( PS\text{-SAR} e PS\text{sppat} \) are reported in tables 1-6.

Considering the employment growth rate, both PS and spatial PS estimates show positive and statistically significant effects. However, adjusting for the spatial bias, the ATT is generally larger than in the standard estimation. Only in the third PSsppat are smaller. The use of the Radius Matching instead of the Kernel Matching confirms the results.

The spatial adjusted effect for the first two PSsppat is around the 35-60% larger than in the not spatially adjusted model: it implies an employment growth rate from 0.9 to 1.5% higher in subsidized local labour system than in not subsidized ones. The data are coherent with a spatial crowding out of employment across subsidized LLSs.

If we evaluate impact of policy on unemployment rate change in the local labour system, we detect a larger effect using spatial propensity score. However, the change is positive in the subsidized LLS indicating an increase of unemployment rate. The differential increase using the special propensity score is small, around 0.2-0.4 points. Probably, the presence of industrial subsidies attracts potential workers from outside of the LLS. The small difference using the spatial propensity score could be imputed to larger frictional unemployment due to an increase in labour opportunities.

The overall effect of policy on economic performance of subsidized areas seems to be lower and not significant, also when we control for spatial effects. Conversely, the specific effect on the manufacturing sector of subsidized areas seems to be positive and significant. However, also in this case the results does not change when we control for spatial effects. The effect on productivity are negative and slightly significant for all sectors, positive on manufacturing sector, without significant changes if controlling for spatial effects.

Considering the employment growth rate, both \( PS \) and \( PS\text{sppat} \) estimates show positive and statistically significant effects. However, adjusting for the spatial bias, the ATT is generally similar to the not adjusted estimation. Only two estimator are larger. The use of the Radius Matching
instead of the Kernel Matching confirms the results.

In general the adjusted PS-SAR and the standard PS are similar, and the results are not statistically different. The spatial adjusted effect using the PS-SAR is more than the 50% larger than in the not spatially adjusted model: it implies an employment growth rate from 2.4 to 3.8% higher in subsidized LLSs than in not subsidized ones. The data are coherent with a spatial crowding out of employment across subsidized LLSs. Using the other spatial PS the impact is generally slightly lower.

If we evaluate the impact on unemployment rate change in the local labour system, we detect a positive effect of the subsidy, indicating an increase of unemployment rate. Probably, the presence of industrial subsidies attracts potential workers from outside of the LLS. Using the spatial PS we estimate a slightly smaller effect. However, the reduction using the SAR-PS is around 0.5 points, but the impact is not statistically significant. The decrease is generally lower using the other spatial PS.
## Effects on labour market

**Table 1** Effects of industrial subsidies on employment growth (1996-2001)

<table>
<thead>
<tr>
<th>Method</th>
<th>Kernel Matching Estimation</th>
<th>Radius Matching Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treated</td>
<td>Control</td>
</tr>
<tr>
<td>PS</td>
<td>190</td>
<td>275</td>
</tr>
<tr>
<td>PSa</td>
<td>190</td>
<td>282</td>
</tr>
<tr>
<td>PSb</td>
<td>190</td>
<td>263</td>
</tr>
<tr>
<td>PS_SAR</td>
<td>190</td>
<td>175</td>
</tr>
<tr>
<td>PS_Spat1</td>
<td>190</td>
<td>282</td>
</tr>
<tr>
<td>PS_Spat2</td>
<td>190</td>
<td>263</td>
</tr>
<tr>
<td>PS_Spat3</td>
<td>190</td>
<td>276</td>
</tr>
</tbody>
</table>

**Table 2** Effects of industrial subsidies on unemployment rate change (1996-2001)

<table>
<thead>
<tr>
<th>Method</th>
<th>Kernel Matching Estimation</th>
<th>Radius Matching Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treated</td>
<td>Control</td>
</tr>
<tr>
<td>PS</td>
<td>190</td>
<td>275</td>
</tr>
<tr>
<td>PSa</td>
<td>190</td>
<td>282</td>
</tr>
<tr>
<td>PSb</td>
<td>190</td>
<td>263</td>
</tr>
<tr>
<td>PS_SAR</td>
<td>190</td>
<td>175</td>
</tr>
<tr>
<td>PS_Spat1</td>
<td>190</td>
<td>282</td>
</tr>
<tr>
<td>PS_Spat2</td>
<td>190</td>
<td>273</td>
</tr>
<tr>
<td>PS_Spat3</td>
<td>190</td>
<td>276</td>
</tr>
</tbody>
</table>

## Effects on economic performance

**Table 3** Effects of industrial subsidies on total value added growth (1996-2001)

<table>
<thead>
<tr>
<th>Method</th>
<th>Kernel Matching Estimation</th>
<th>Radius Matching Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treated</td>
<td>Control</td>
</tr>
<tr>
<td>PS</td>
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<td>275</td>
</tr>
<tr>
<td>PSa</td>
<td>190</td>
<td>282</td>
</tr>
<tr>
<td>PSb</td>
<td>190</td>
<td>263</td>
</tr>
<tr>
<td>PS_SAR</td>
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<td>175</td>
</tr>
<tr>
<td>PS_Spat1</td>
<td>190</td>
<td>282</td>
</tr>
<tr>
<td>PS_Spat2</td>
<td>190</td>
<td>273</td>
</tr>
<tr>
<td>PS_Spat3</td>
<td>190</td>
<td>276</td>
</tr>
</tbody>
</table>
7. Conclusions

The main aim of this paper is to make the empirical evaluations of business subsidies programs more thorough and more pertinent to the policymakers’ targets. We propose a new method to evaluate place based policies which intend to avoid biased ATT estimates and consider the principal spillover effects in the estimates. The method is based on a spatial PS, that takes into account the spatial linkages across subsidized and not subsidized areas. In this paper we have applied the new method on the evaluation of the two more important measures for local development in Italy: incentives by Law 488/92, mainly devoted to SME, and Planning Contracts, created for large projects. The analysis is based on a spatial propensity score matching applied to a very disaggregated territorial grid. A spatial DID Matching model is estimated using different econometric approach, taking into account the endogeneity of spatial linkages. The identification strategy of the unbiased ATT estimates is based on the introduction of spatial externalities in the propensity score. Empirically, we assume that the matching is correct only if the treated LLS and the not treated ones have the same number or share of treated neighbours or neighbours with the same probability to be subsidized.

The basic idea in the paper is that the effect of the policy intervention is twofold: on one side, there is a direct effect on subsidized firms, that is generally positive, the output effect outweighing the substitution effect; on the other side, there is a (usually positive) crowding out effect across firms in the same area and across neighbouring areas. In this case the SUTVA hypothesis is clearly not valid.. Assuming that the treated LLS and not treated ones have neighbours that are similar with respect to the treatment, we also assume that crowding out effect across neighbouring LLS are also similar. Therefore our method allows to detect the direct effect of the program on subsidized LLS, netting out the indirect effects.

Our nonparametric results are close to the results obtained using parametric methods, as in De Castris and Pellegrini (2005). Basically, Law 488/92 and Planning Contracts have achieved the (implicit or explicit) targets selected by the policy makers. However, the spillovers are concentrated on the labour market: only for employment and unemployment we find some differences between the standard PS and the spatial PS approach.

The results are consistent with the interpretation presented in Cerqua and Pellegrini (2014): in the
factor market there is labour mobility to some extent, but the substantial relocation costs make capital, a very deep-rooted factor (at least in the short-run). Additionally, in the product market, firms located in the same area compete on the same job market, but they often do not compete on the same product market. Therefore, it is plausible that spillovers are much stronger for employment than for capital or product. Our findings are extendable to policies similar to Law 488/92, that rewards projects with a high labour component.

The positive impact of subsidies on regional employment growth is also coherent with most of the literature. However, the results show that the impact of subsidies on regional growth could be larger in case of controlling for the presence of spatial effects. Therefore the empirical analysis suggests the presence of some subsidies’ spatial crowding-out, where subsidized areas attract employment and firms from neighbourhoods.

A clear policy implication of the paper is that the evaluation of the spatial effect of the policy intervention should be based on the spatial net effect that considers the generally positive effects on the subsidized areas but also the crowding out effect in the neighbouring areas. Moreover, the analysis suggests that selective subsidies programs, like Law 488/92 and Planning Contracts, appear to be useful and effective for regional development.
References


