

Evaluation of net spatial effects of public subsidies¹

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Abstract: The paper intends to identify the territorial effects of industrial subsidies implementing a matching procedure based on a ‘spatial propensity score’ (SPS). The hypothesis is that probability to get incentives depends on probability to get incentives in neighbouring areas. The innovative idea of the paper is an instrumental variable estimator applied to a probit model. The empirical analysis refers to data on subsidies by Law 488/92 and program agreement, classified by local labour system. The results show a positive average effect stronger than that got by traditional econometric methods.

Keywords: propensity score matching, spatial analysis

1. Introduction

The literature about the quantitative evaluation of spatial effects of industrial aid schemes is not extensive. There are very few papers that analyze the spatial diffusion of industrial policies based on (capital) subsidies to private firms (De Castris and Pellegrini, 2005, 2008). 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 establish conclusively 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 and treatment effects, using the Rubin Causal Model set up with potential outcomes (Rubin, 1974), rather than the regression framework that is generally used in this literature. The presence of a spatial interaction means that the effects of a subsidy in a region also affect the more contiguous regions. In this case the stable unit treatment value assumption (SUTVA) is not valid and some econometric methods should be used in order to correct the analysis for the presence of spatial dependence.

The focus of our paper is to identify the regional effects of industrial subsidies when the presence of subsidized firms is spatially correlated. We propose a novel “spatial propensity score matching” technique that allow to correct for the spatial bias. The new estimator is applied on a new 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 program agreement

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(contratti di programma), created for large projects. 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 for spatial effects, specifying an appropriate spatial model.

2. Methodology

The evaluation problem in the paper is to measure the impact of industrial policy program on an outcome variable (Y) for each territory. The impact is defined as the difference between the value of Y observed on the units after the intervention and the value of Y would have taken if the same unit had not being treated, the so called counterfactual. In our study the treated units are represented by those local labour systems where subsidized firms are localized. The counterfactual units are therefore units that should represent what would be happen in treated units in absence of treatment. The choice of the best estimator to implement in the evaluation analysis is, however, not immediately univocal. Using a parametric approach, the impact is evaluated through an econometric estimation of a function, usually linearly specified. Then, the evaluation results are critically dependent on assumptions about functional forms, and this tends to generate substantial biases in several cases.

A non parametric approach, such as matching estimator proposed by Rosenbaum and Rubin (1983) and developed in several evaluation papers (see Blundell and Costa Dias, 2008) may be better because it allows control for potential bias due to non random selectivity into the policy intervention. 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 method estimator (MM) is given by:

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

where Y_i and Y_j are the post-program outcomes for subsidized and non subsidized LLSs, respectively; ω_{ij} is a weight indicator of the similarity between the two LLSs before the subsidy was provided and ω_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 propensity score and this variant of matching is well-known as “propensity score matching”. Any standard probability

model can be used to estimate the propensity score (p), such as for example $p = Pr\{T_i = 1|X_i\} = F(h(X_i))$ where $F(.)$ is the normal or the logistic cumulative distribution and $h(X_i)$ is a function of covariates.

The estimation of a “classical” propensity score in our empirical application shows that the residual are spatially correlated. The reason is the presence of a spatial crowding out: 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. In this case the probability of LLS to be treated (to have a substantial share of investments that is subsidized) depends on the probability that the contiguous LLSs are treated. From an econometric point of view, the problem can be deal with estimating an appropriate spatial lag model (Anselin, 1988) for the spatial propensity score (p_{spat}).

A generic specification is $p_{spat} = F(h(X_i), g(W^* p_{spat}))$, W is the usual spatial weights matrix where w_{ij} is equal to 1 if the distance between two centroids of LLS is less than 50 km, the average distance between the centroids, 0 otherwise. The coefficient of $W^* p_{spat}$ cannot be estimated by a simple probit/logit model, given the effect of error term on $W^* p_{spat}$. Our approach is to use an IV estimator, instrumenting the $W^* p_{spat}$. Given a correct estimate of p_{spat} , a usual matching approach can identify the effects of industrial scheme on the outcome.

Another problem is to identify the subsidized LLS. Actually subsidized firms are localized in almost all the considered LLS but the effect of the intervention can be detected when it represents a significant share of the investment realized in the LLS. So we consider as subsidized areas the LLS having a share larger than 5% of subsidized investment. However, our dataset contains only employment (and not total investment). Therefore LLS is treated if the subsidized new employment is larger than the 5% on the total new employment in manufacturing.

3. Results

We estimated a 2-stage probit model with endogenous regressors: at the first stage $W^* p_{spat}$ is instrumented, using the exogenous covariates and their spatial lag. The result is plugged into the second stage equation. Using the spatial propensity score, we implemented the matching algorithm in order to identify the average treatment effect on treated (ATT) with respect to employment dynamics. Therefore ATT is estimated using a DID Matching estimator (MDID) that can provide better performance than traditional matching estimators (Blundell and Costa Dias, 2008). The MDID is implemented by a Kernel matching estimator and a Nearest Neighbour matching estimator. The standard errors of the ATT are estimated by the bootstrap procedure (1000 replications) described in Becker and Ichino (2002). The classical propensity score is estimated using as covariates: unemployment rate (1996), share of agricultural employment (1996), value added growth rate in service sector (1996-2001), employment growth rate in period 1991-1996, dummy for southern regions, dummy for urban LLS. The estimated model is statistically significant and the pseudo r-square of the equation is 0.11. The balancing property is satisfied. 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. However, the result reflects the spatial correlation of incentives (Moran Index I equal to 0.197, strongly significant). We have estimated the spatial propensity score, including

in the probit model the spatial lag of the covariates (excluding the growth rate of service sector) and the spatial lag of the dependent variables. The last variable has been instrumented, using as instrument the exogenous covariates. The estimated model is statistically significant, and the adjusted r-squared is 0.49. Therefore the spatially lagged variables improve strongly our estimation. The two estimated propensity score are used in order to detect the average effect of subsidies on the employment growth rate in the local labour system. The two matching estimators are used, and the results are reported in Table 1. In both cases the effects are positive and statistically significant. However, adjusting for the spatial bias, the ATT is clearly larger than in the not adjusted estimation. The spatial adjusted effect is around the 40% larger than in the not spatially adjusted model: it implies an employment growth rate from 3.6 to 5.6 per cent higher in subsidized local labour system than in not subsidized ones. Our non parametric results are close to the results obtained using parametric methods, as in De Castris and Pellegrini (2005). On the whole, Law 488/92 and Program Agreements have achieved the (implicit or explicit) targets selected by the policy makers. The subsidized firms have invested more than usual, and they have increased the number of employees more than those non subsidized. The positive impact of subsidies on regional employment growth is also coherent with most of the literature.

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

	Kernel matching estimation					Nearest Neighbour Matching Estimation				
	Treated	Control	ATT	S.E.	t	Treated	Control	ATT	S.E.	t
Empl. growth (p)	190	283	0.026	0.013	2.02	190	107	0.04	0.019	2.08
Empl. growth (pstat)	190	264	0.036	0.015	2.35	190	95	0.056	0.018	3.22

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