Policy Evaluation and Spillover Effects

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Abstract

SUTVA represents the golden rule in evaluating causal effects, even if it does not allow to estimate spillovers. To overcome this limitation, this paper proposes a framework for causal inference in presence of spatial interactions within a new Spatial Hierarchical Difference-In-Differences model (SH-DID). This approach decomposes the ATE by identifying direct and indirect treatment effects. Montecarlo Simulations demonstrate how ATE in traditional causal model is still correct even in presence of interferences, while direct and indirect estimates are biased. Conversely, SH-DID provides unbiased estimates of both total, direct and indirect effects. On this basis, we provide empirical evidence on the effectiveness of public policies in Italy. We found an additional impact of the policies on R&D expenditures. Decomposing the ATE we demonstrate positive and significant direct effects, while the indirect impact is negative and meaningful, even if limited to treated units.

1 Introduction

In recent years, R&D policies cover an increasingly relevant role in stimulating innovation. Moreover, EU Commission aims to foster a *"smart, sustainable and inclusive growth"* by developing "smart specialization" strategy (Foray et al., 2011). Smart specialization[1] is a "place-based" policy approach which requires that regions are able to identify, through an entrepreneurial discovery process, the areas where they can better innovate and build up international comparative advantages (von Tunzelmann, 2009). Efficient Smart specialization policies rely on the concepts of embeddedness and connectedness. This approach, based on the implementation of ad-hoc local policies, takes into account that innovation is rooted into localised and long-term processes[2] and embedded in human capital, interpersonal network and skilled labour markets (Camagni and Capello, 2013).

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[1]McCann and Ortega-Argilés (2013) propose an interesting review of the rationale behind the reforms of EU cohesion policies. The aforementioned authors distinguish between two different perspective to analyse the novel policies approach: a rethinking of the role of industrial policy and the understanding of the relationship between economic geography, institutions and technology. However, in this paper we will focus only on the development of linkages between economical agents.

[2]In-depth analysis on the geographical dimension of innovation systems is in: Jaffe et al. (1993); Feldman (1994); Audretsch and Feldman (1996); Breschi and Lissoni (2001); Porter (1998); Fritsch and Slavtchev (2011).

Innovation-related knowledge flows are embodied in both face-to-face interactions and the mobility of human capital (McCann and Ortega-Argilés, 2015). From this viewpoint, sectoral and spatial linkages becomes essential to foster knowledge spillovers and, in wider term, innovation. However, the interest on spillover effects is not limited to policy-makers, but becomes a central pillar in both causal analysis and policy evaluation.
Nonetheless, the inclusion of indirect effects in the traditional framework is not straightforward and can still be considered as one of the main challenges for the researchers. Indeed, it requires a substantial redefinition of the role covered by interactions between units. Identification of causal effects typically relies on the validity of the SUTVA[3] (Rubin, 1980) which imposes the absence of interferences between units (Cox, 1959). For this reason, in traditional experimental approaches, interferences are considered as nuisances, while major efforts are devoted to design analysis able to isolate the presence of interferences from causal effects. Consequently, SUTVA does not allow to identify and estimate indirect treatment effects.
Moreover, place-based policies points towards the formation of spatial and social linkages between economic agents and the development of methodologies able to evaluate the effects of interferences makes the SUTVA a streamlined assumption. In the remainder of this paper we provide an in-depth analysis of the literature focuses on the violation of the ”no-interferences” assumption. Moreover, the major innovation introduced in our work consists in the evaluation of both direct and indirect (i.e. spillovers) treatment effects on Italian R&D expenditures. The estimates are implemented by a novel Spatial Hierachical Diff-in-Diff (SH-DID) estimator. This approach directly includes spatial interferences in the regression model of Difference-in-Difference estimator.

2 Review of the Literature

The identification and estimation of direct and indirect effects requires an exhaustive investigation of policy evaluation empirical studies and, in wider term, causal analysis in presence of interferences[4]. First and foremost, it is fundamental to define the concepts of direct or indirect effects. Hudgens and Halloran (2012) define the *”direct effect”* as the response of the agents to the treatment, while the *”indirect effect”* are the response to the interferences. Moreover, the knowledge of spillover effects not only ensure unbiased estimates of treatment effects, but it plays a central role in the cases in which treatment induces interaction.
Rosenbaum (2012) argues that interferences can be *"unlimited in extent and impossible to specify in form"*. To limit the extension of interferences, economic theories consider different measures of proximity, including geographical distance, nodal distance in a social network, metrics of social or economical distance (Hong and Raudenbush, 2012). Furthermore, Manski, in the so-called *”Reflection Problem”*, observes how the presence of interferences does not allow to distinguish

[3] The value of the outcome for unit i when exposed to treatment t will be the same regardless of the treatments that other units receive (Rubin, 1974).
[4] See Zúñiga-Vicente et al. (2014) and Becker (2015) for recent survey on policy evaluation studies.

between endogenous, exogenous and correlated effects, making impossible the identification of the spillovers (Manski, 1993, 2013). Notwithstanding, Corrado and Fingleton (2012) and Gibbons et al. (2014) argue that hierarchical and spatial econometrics approaches enable to deal with the reflection problem. Theoretical and empirical analyses considering the potential outcomes framework and its associated assumptions in a spatial context are still few and far between.
Sinclair et al. (2012) develop an alternative approach within a multilevel framework. This method considers a hierarchical trial in which treatments are randomly assigned to individuals and, varying proportions of their neighbours, provides evidence of within-household spillovers in a large-scale voter-mobilization experiment conducted in Chicago. Notwithstanding the relevance of the contents, literature considering spatial interferences in policy evaluation studies is still uncommon. De Castris and Pellegrini (2015) estimate the ”net” effect of Italian R&D subsidies based on a novel ”spatial propensity score matching” technique. The authors observe a positive even if small crowding out effect across firms in the same area and within neighbouring areas.
Arpino and Mattei (2013) model interactions as a function of the characteristics of the units. This function considers different factors, including geographical distance between the firms and their sizes. In the case of small hand-craft firms in Italy, the aforementioned authors demonstrate that additionality is reduced when treated firms are subject to high levels of interference. Moreover, the average causal effect is slightly underestimated when interferences are ignored.
In this paper we identify and estimates the indirect effects by developing a novel causal approach. This method, modelling the presence of spatial interferences in a Difference in Difference framework, allows to decompose the average treatment effect estimating separately both direct and indirect causal impacts. Moreover, the major innovation of this approach consists in the possibility to evaluate differentiated indirect effects between treated and controls.

3 Introducing the Interferences in DID approach

As widely recognized in causal analysis, Diff-in-Diff estimators provide correct estimates of the treatment effect, even if do not allow to consider the inferences between units. In this sense, we implement a novel regression model which considers interferences by including additional components in the ”standard” DID estimator multiplied by the state of treatment of the neighbours units[5]. This allows to obtain the specification in 1:

$$Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j D + \beta_6 D_j Dt \tag{1}$$

[5] Verbitsky-Savitz and Raudenbush (2012) was the first to approximate interactions between units by considering treatment assignments of all the units in the potential outcome.

Using the specification in 1 we are able to estimate simultaneously both total, direct and indirect causal effects. In this way the formulation of the ATE becomes:

$$ATE = \beta_3 + \beta_4(\overline{D_j^1} - \overline{D_j^0}) + \beta_6 \overline{D_j^1} \tag{2}$$

The term $\overline{D_j^1}$ (resp. $\overline{D_j^0}$) indicates the average share of treated neighbours for subsidized (resp. control) units. ATE in 2 is obtained applying a double difference estimator conditioning for own state of treatment and time. The identification of direct and indirect effects requires an introductory presentation of all the possible results obtainable conditioning with respect to time, own and neighbours' state of treatment. The cases in which $D_j \neq 0$ represents the situations in which we assume that the treatment induces interactions between units, i.e. in the neighbourhood of the considered unit is located at least one treated unit. From 1 we derive the impact of direct and indirect causal effects:

$$\begin{aligned}
a &= E[Y|D=1, t=1, D_j \neq 0] = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 \overline{D_j^1} + \beta_5 \overline{D_j^1} + \beta_6 \overline{D_j^1} \\
b &= E[Y|D=1, t=1, D_j = 0] = \beta_0 + \beta_1 + \beta_2 + \beta_3 \\
c &= E[Y|D=1, t=0, D_j \neq 0] = \beta_0 + \beta_1 + \beta_5 \overline{D_j^1} \\
d &= E[Y|D=1, t=0, D_j = 0] = \beta_0 + \beta_1 \\
e &= E[Y|D=0, t=1, D_j \neq 0] = \beta_0 + \beta_2 + \beta_4 \overline{D_j^0} \\
f &= E[Y|D=0, t=1, D_j = 0] = \beta_0 + \beta_2 \\
g &= E[Y|D=0, t=0, D_j \neq 0] = \beta_0 \\
h &= E[Y|D=0, t=0, D_j = 0] = \beta_0
\end{aligned} \tag{3}$$

The direct effect (ADTE) is estimated by the Diff-in-Diffs for the units without treated in their neighbourhood, i.e. the ADTE represents the situation in which there are not interactions due to the treatment. In this way we obtain the ADTE as in 4:

$$ADTE = b - d - f + h = \beta_3 \tag{4}$$

Furthermore, model specification allows for differentiated indirect effect both on treated and controls. The indirect effects are obtained through a double difference estimator on time and neighbours state of treatment, maintaining constant the own state of treatment.

$$AITET = a - c - b + d = \beta_4 \overline{D_j^1} + \beta_6 \overline{D_j^1} \tag{5}$$

$$AITENT = e - g - f + h = \beta_4 \overline{D_j^0} \tag{6}$$

5 and 6 represent respectively the AITET (Average Indirect Treatment Effects on the Treated) and the AITENT (Average Indirect Treatment Effects on the Controls). In this paper we analyse the correctness of the intuition behind the DID model with interferences. In the next section we present the results of our simulation.

4 Montecarlo Simulation

To provide a brief illustration of the performance of our approach, we consider 100 and 250 Monte Carlo replications for the cases of 225, 400 and 625 units. According to the literature, spatial econometrics tools and hierarchical modelling allows to overcome the identification problems related to the presence of interaction between units. For this reason we compare the efficiency of a linear, a spatial and a hierarchical model. The simulated data consider a clustered spatial distribution of the units. Moreover, we take into account possible differences between areas through the inclusion of a random neighbourhood effect. This stratified approach makes possible the introduction of a spatial hierarchical model. This assumption produces a realistic framework, in which the spatial distribution of the units presents both clustered and undeveloped areas. Furthermore, the inclusion of a hierarchical model has a twofold relevance. On one hand, multilevel approach allows to overcome the identification problem in presence of interferences (Corrado and Fingleton, 2012). On the other hand, hierarchical model controls for the presence of heteroskedasticity both at unit and neighbourhood level improving the efficiency of the estimates. To propose a unique framework able to provide correct total, direct and indirect effects we develop the following DGP:

$$
\begin{cases}
y_i = \alpha + \beta X + \epsilon_j + u_i \\
u_i = \lambda W u_i + \epsilon_i \\
\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6) = (1, 1, 1, 0.1, 0.1, 0.1) \\
X = (D, t, Dt, D_j t, D_j D, D_j Dt) \\
\lambda = 0.5 \\
D_j = WD \text{ with W considering the presence in neighborhood} \\
D_j = d \in [0, 1] \\
\epsilon_i \sim N(0, 0.1) \\
\epsilon_j \sim N(0, \sigma_j^2)
\end{cases}
$$

Our DGP considers a spatial weight matrix W build at neighbourhood level. Moreover, we consider a spatial error model with neighbourhood random effects. Under previous hypotheses, we are able to estimate intra-clusters indirect effects.

Results of the DID with interferences (Table 1) show better performances of the multilevel approach for all the considered sample sizes and number of simulations. Indeed, hierarchical model provides unbiased direct and indirect effects compared to both linear and spatial procedures. This model, controlling for the presence of spatial heteroskedasticity at neighbourhood level, entails a substantial reduction of the standard errors and an improvement of the quality of our estimates. Nevertheless the multilevel model is a correct estimator of the Diff-in-Diffs in presence of interferences, spatial and linear model reduce their bias for high sample size and number of simulations. Furthermore, to demonstrate the superiority of the hierarchical approach we look at the distribution of the results by comparing the performances of the three methodologies.

Table 1: Results Novel DID with neighbourhood effects

			DID		Spat-DID		SH-DID		
	n	m	Result	S.Error	Result	S.Error	Result	S.Error	True
Cons			0.9950	0.0124	0.9967	0.0523	0.9975	0.0521	1
D			0.9985	0.1134	0.9961	0.0618	0.9970	0.0540	1
t			0.9883	0.0272	0.9913	0.1343	1.0000	0.0134	1
Dt	225		1.0117	0.1620	1.0015	0.0886	1.0000	0.0640	1
Djt			0.1320	0.0554	0.1208	0.2539	0.1001	0.0303	0.1
DjD			0.1235	0.2271	0.1083	0.1264	0.1064	0.1101	0.1
DjDt			0.0680	0.3268	0.0982	0.1797	0.0999	0.1296	0.1
Cons			1.0009	0.0069	0.9991	0.0271	0.9991	0.0270	1
D			0.9813	0.0552	1.0048	0.0425	1.0052	0.0372	1
t			1.0136	0.0150	1.0145	0.0718	1.0001	0.0104	1
Dt	400	100	0.9864	0.0789	0.9989	0.0605	0.9999	0.0440	1
Djt			0.0642	0.0302	0.0668	0.1374	0.0997	0.0235	0.1
DjD			0.1292	0.1085	0.0911	0.0862	0.0904	0.0751	0.1
DjDt			0.1358	0.1566	0.1006	0.1221	0.1003	0.0881	0.1
Cons			1.0002	0.0044	1.0002	0.0131	1.0006	0.0130	1
D			0.9891	0.0321	0.9959	0.0328	0.9960	0.0290	1
t			0.9998	0.0103	0.9994	0.0370	1.0001	0.0097	1
Dt	625		1.0002	0.0461	0.9999	0.0466	1.0000	0.0348	1
Djt			0.1005	0.0204	0.1017	0.0702	0.0999	0.0213	0.1
DjD			0.1210	0.0625	0.1064	0.0661	0.1062	0.0582	0.1
DjDt			0.0995	0.0908	0.1003	0.0937	0.1001	0.0691	0.1
Cons			0.9942	0.0122	0.9940	0.0501	0.9949	0.0497	1.0
D			0.9593	0.1008	0.9994	0.0549	0.9991	0.0482	1.0
t			0.9996	0.0270	0.9961	0.1295	1.0001	0.0137	1.0
Dt	225		1.0004	0.1441	0.9994	0.0789	0.9999	0.0577	1.0
Djt			0.1008	0.0547	0.1097	0.2452	0.0998	0.0312	0.1
DjD			0.1775	0.2007	0.0981	0.1127	0.0988	0.0986	0.1
DjDt			0.0992	0.2896	0.1015	0.1606	0.1003	0.1170	0.1
Cons			1.0000	0.0070	0.9993	0.0273	0.9994	0.0272	1.0
D			0.9720	0.0560	0.9994	0.0436	0.9999	0.0382	1.0
t			1.0063	0.0151	1.0043	0.0716	1.0000	0.0107	1.0
Dt	400	250	0.9937	0.0801	0.9998	0.0620	0.9999	0.0454	1.0
Djt			0.0826	0.0307	0.0894	0.1374	0.0999	0.0244	0.1
DjD			0.1550	0.1105	0.1025	0.0886	0.1014	0.0774	0.1
DjDt			0.1174	0.1594	0.0999	0.1255	0.1001	0.0913	0.1
Cons			0.9973	0.0043	0.9972	0.0125	0.9974	0.0125	1.0
D			1.0012	0.0301	0.9998	0.0311	0.9998	0.0276	1.0
t			1.0014	0.0100	1.0014	0.0352	1.0001	0.0097	1.0
Dt	625		0.9986	0.0433	0.9997	0.0443	0.9999	0.0334	1.0
Djt			0.0963	0.0200	0.0966	0.0673	0.0997	0.0214	0.1
DjD			0.0963	0.0588	0.1000	0.0632	0.0999	0.0558	0.1
DjDt			0.1037	0.0856	0.1005	0.0896	0.1003	0.0668	0.1

Figure 1: Density parameter in the neighbourhood of the true value

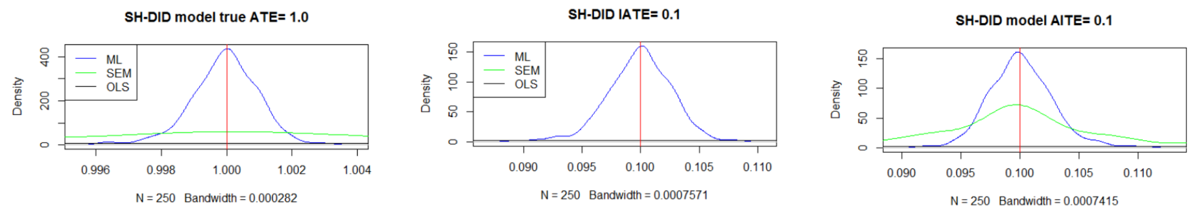
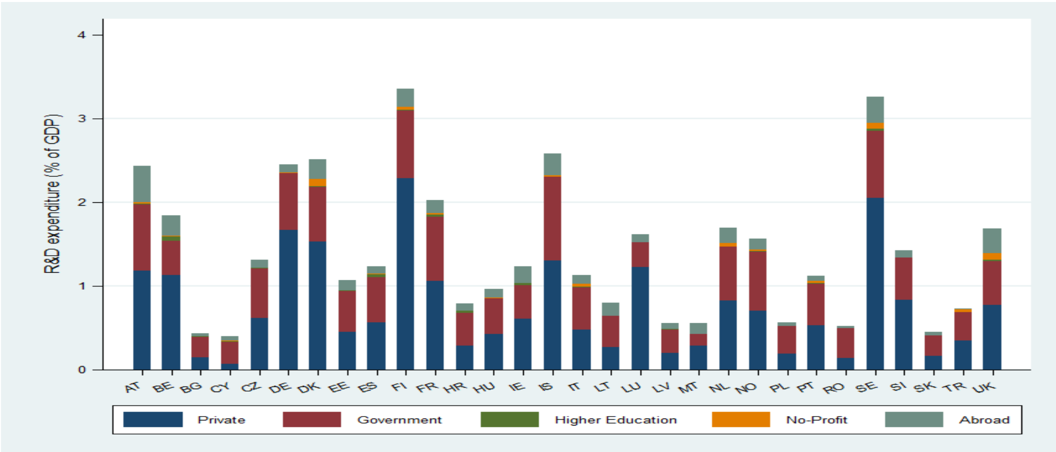


Figure 1 shows the distribution of the parameters β_3,β_4 and β_6 over the different replications. Looking at distributions it appears clearly how multilevel approach exhibits a maximum on the true value of all the parameters and presents the less dispersed distribution in comparison with the other two estimators. While spatial approach can be considered a satisfying approximation of the expected result, linear procedure provides an unbiased estimates of total indirect effects, even if it does not distinguish correctly between the treated and controls parameter. Furthermore, ATE estimates in linear Diff-in-Diff is still unbiased. For this reason, on the remainder of this work we consider only linear and spatial-hierarchical models.

5 Empirical Strategy

In recent years, Eu Commission underlines the relevant role played by R&D and innovation to foster growth. Notwithstanding, public and private R&D expenditures remain stable over the last decade and far from the 3% objective specified in the Horizon 2020 plan.

Figure 2: European R&D Expenditures by source of funds



Source: Eurostat
Note: Figure 3 shows the R&D expenditures in EU by source of funds in GDP percentage for the year 2007.

Figure 2 remarks the European lack of investments in innovation. In this context, Italy exhibits R&D expenditures below European average, regardless of the source of funds. More in detail, in 2007 Italy invests the 0.61 % of the GDP in private R&D, while the 0.52 % of the GDP is devoted to public expenditures. The inadequate effort on R&D appears evidently comparing Italian and European averages. Indeed, EU private and public R&D is, respectively, equal to 1.17 and 0.66 of the GDP. As we will explain later, in this section we take into account the data on R&D expenditures for the 2007 to focus on the pre-treatment period.

The lack of R&D investments and the territorial gap between Northern and Southern regions (MISE, 2015) has required a strong intervention both at European and National level. During 2007-2013, Italy is the third largest beneficiary of the European Union's Cohesion Policy after Poland and Spain, receiving a total of almost €29 billion in European aid (from the European Regional Development Fund (ERDF) and the European Social Fund (ESF)) under the Convergence, Regional Competitiveness and Employment and European Territorial Cooperation Objectives [6]. Table 2 resumes the total amount of public funding in Italy between 2007-2013. The country-wide

[6]The Convergence Objective concerns regions characterised by low levels of GDP and employment, where GDP per head is less than 75% of the EU average. It applies to 99 regions representing 35% of the EU-27 population and aims to promote conditions conducive to growth and ones which lead to real-time convergence in the least-developed Member States and regions. The Regional Competitiveness and Employment Objective is applicable to the rest of the EU, or to 172 regions, representing 65% of the EU-27 population. It aims to enhance the competitiveness and attractiveness of regions, as well as boost their employment levels. The Italian Convergence Regions are Campania, Apulia, Calabria, Sicily and Basilicata.

Table 2: Funds for Italy in Billion €2007-2013

Objective	Fund	EU	National Public	Total
Convergence	ERDF	17.8	18	35.8
	ESF	3.7	3.9	7.6
Total Convergence		21.5	21.9	43.4
Regional Competitiveness and Employment	ERDF	3.1	5	8.1
	ESF	3.2	4.4	7.6
Total Reg. Competitiveness and Employment		6.3	9.4	15.7
Total European Territorial Cooperation	ERDF	1	-	1
TOTAL		28.8	31.3	60.1

Source: EU Commission
Note: Figures have been rounded up.

financial commitment consists of €60 billion, fairly subdivided between European and National funds. On the whole, Italy has defined 66 programmes:

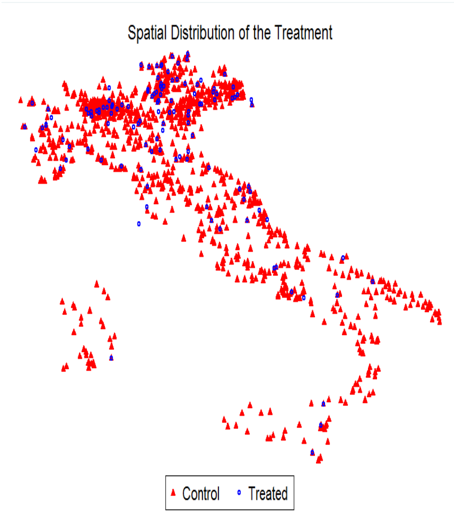
- 19 programmes under the Convergence objective, with 10 programmes managed at regional level, seven at national level and two interregional programmes;
- 33 programmes under the Regional Competitiveness and Employment objective (32 programmes managed at regional level and one managed at national level);
- 14 programmes under the European Territorial Cooperation Objective.

Investment in R&D and innovation constitutes the greater part of overall investment. In fact, Italy allocates €9.6 billion to this priority, in particular through the "Research and Competitiveness" programme. In this work we provide evidence on additionality of public incentives supplied to Italian firms. In detail, we evaluate policy effectiveness on R&D expenses and the possible occurrence of spillover effects due to the exposition of neighbours' state of treatment. R&D expenses are introduced in our analysis by two different waves of the CIS[7] : 2008 and 2010. This data are modelled on harmonized questionnaires at European level, therefore the results of the Italian case can be easily extended and compared with studies based on different countries.
The definition of an appropriate dataset requires a preparatory identification of the firms which have reply to both the CIS waves considered. This process allows to individuate more than 7000 firms. Considering indirect effects requires the geo-localization of all the companies along Italian territory. Given the lack of informations on the exact spatial point in which the firms are located, we determine the geographical coordinates at municipal level (i.e. every firms located in the same city have same coordinates), while the outcome variables and the treatment are still considered at firm level. Moreover, the definition of treatment group does not distinguish between European, national and regional incentives. In this way, we are able to include all the incentives provided to

[7]The Community Innovation Survey (CIS) are carried out with two years' frequency by EU member states and number of ESS member countries. The CIS is a survey of innovation activity in enterprises. The harmonised survey is designed to provide information on the innovativeness of sectors and on various aspects of the development of an innovation, the public funding, the innovation expenditures, etc. (Eurostat).

the firms in order to avoid the presence of treated units in control group[8].
Conversely, the correct identification of a pre and post treatment period required the exclusion from the sample of all the firms subsidized on 2008 or on both periods. We limit our analysis to SMEs and, to check for systematic differences between the two samples, we implement a propensity score on sectoral, dimensional and territorial variables. Moreover, we avoid to consider units in the extremes of the distribution of the propensity score. Clearly this operation improves the quality of our estimates; but reduces the overall sample size to 2389 SMEs, of which only 145 treated.

Figure 3: Spatial Distribution of the firms



Note: This figure represents the spatial distribution of the firms, distinguishing between treated and control.

Figure 3 shows the geographical localization of the firms. The majority of the units are located in Italian northern regions, even if the presence of isolated treated, especially in Southern and Insular Italy, has interesting implication on the results. In further detail, the foregoing insight enables to check for two extreme cases: lack or high level of interferences. In addition, including southern Regions allows to consider Obj.1 policies.

The summary statistics at baseline period shows some structural differences between treated and control groups, both in terms of size and propensity to innovation. This outline can be, at least, partially influenced by the limited sample size of the treated group. However, the implementation of a Difference in Difference approach allows to check and remove systematic differences between the groups.

[8]For example, limiting the analysis on regional subsidies we are able to define an appropriate control group. Notwithstanding, the firms not subsidized can obtain incentives administered at national or European Level invalidating the correctness of our results. Otherwise, considering all the different level of incentives we are able to define correct treated and control group and obtain unbiased estimates.

Table 3: Summary Statistics

Variables	Control			Treated		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Turnovers 2006	2244	6095743.00	6471570.00	145	8022972.0	7113732.0
Employees 2006	2244	32.21	28.00	145	47.2	34.1
Presence in Local Market	2244	0.94	0.23	145	0.9	0.3
Presence in National Market	2244	0.53	0.50	145	0.8	0.4
Turnover share from innovation for the market	2244	0.02	0.09	145	0.2	0.2
Turnover share from innovation for the firms	2244	0.03	0.13	145	0.1	0.2
Turnover share from marginal innovation	2244	0.96	0.29	145	0.7	0.3

Source: Control Covariates for baseline period (2008)

5.1 Econometric Model

To ensure robust and unbiased estimates of both direct and indirect effects we follow the approach in Section 4. As previously explained, the introduction of an alternative hierarchical specification, with heterogeneity at municipal level considered in the random effects, is required to provide unbiased estimates of both indirect effects on treated and controls. Resuming, in this paper we apply 5 different estimation procedures (reported in the results with numbers between 1 to 5):

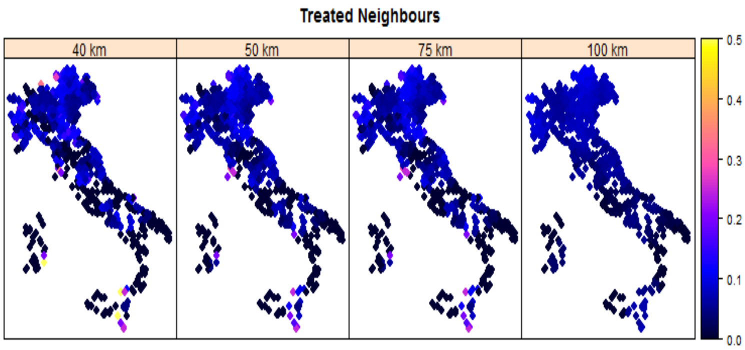
1. $Y = \beta_0 + \beta_1 D + \beta_2 T + \beta_3 DT$
2. $Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j D + \beta_6 D_j Dt$
3. $Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_6 D_j Dt$
4. $Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j D + \beta_6 D_j Dt + \epsilon_j$
5. $Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_6 D_j Dt + \epsilon_j$

The firsts 3 models are estimated by linear procedure, while the latter 2 are evaluated by a spatial-hierarchical approach. More specifically, model 1 represents the traditional ”Diff-in-Diff” and it constitutes the benchmark for ATE estimates. The presence of interferences are considered in all the remaining cases. Furthermore, models 2 and 3 (resp. 4 and 5) differing by the removal of systematic control for the presence of heterogeneity due to the interactions between own and neighbours state of treatment. This approach allows us to draw attention on the role played by heterogeneity at neighbourhood level on the unbiasedness of indirect effects estimates.
The behaviour of treatment effects over space is investigated by 4 different spatial weight matrix based on the following cut-off distances: 40 km, 50 km, 75 km, 100 km. The smallest cut-off distance (i.e. 40 km) enables to consider the case in which every firm has at least one neighbour (i.e. no island). Taking into account different cut-off distances, the geographical extension of both direct and indirect effects is properly evaluated. This procedure permits to obtain information on the optimal dimension of the spillovers over the space.

6 Results

The effectiveness of the treatment is computed using the informations from Community Innovation Surveys. Taking into account the short time frame between pre and post treatment period, we investigate only the results on R&D expenditures. In fact, it is reasonable to expect in first instance an additional impact on innovation expenses, while the evaluation on R&D outputs and economic performance can require a longer time period. In other words, we are not able to properly analyse economic performances in our short term analysis.
Thus, our study is restricted on the evaluation of the effects on total R&D, internal R&D and external R&D. These variables provides detailed information on innovation and R&D processes.
Figure 4 analyse the share of treated neighbours for all the firms included in our analysis along

Figure 4: Spatial distribution of the proportion of treated neighbours



Note: Figure 5 shows the different quotas of treated neighbours for each firms when we consider different cut-off distances. The considered cut-off are: 40 km, 50 km, 75 km, 100 km.

Italian territory. Every panel represents a different cut-off distances. This procedure makes possible an in-depth analysis on the impact of the distance on D_j. For small distances, it appears a limited number of firms characterised by high level of spatial interferences (i.e. yellow and purple units), while the majority of them present low shares of treated neighbours (dark blue). Conversely, increasing cut-off distances implies a reduction, on average, of the strength of spatial interferences. In detail, for a cut-off of 100 km the spatial distribution exhibits low levels of interferences (more or less between 0.0 and 0.15). The shortcoming of long-distance interactions highlights possible linkages between physical distance and diffusion of the indirect effects[9].

The discussion results consists of a step-by-step analysis. Firstly, we focus on the total impact of the treatment (model 1). ATE in model 1 constitutes the benchmark for the decomposition process. The estimates demonstrate positive and significant total effects for almost all the outcome

[9]To give an example: we can imagine three different firms (A,B and C) located along a straight line and only one of them (A) is treated. The distance between A-B is 20 km, while A-C is 50 km far. It seems reasonable to assume that indirect effect of being subject to the treatment of A decreases with the distances. Thus, we expect a greater impact on B.

Table 4: Decomposition of the ATE

			40				50				75				100			
			ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE
OUTCOME	Total R&D	[1]				210227.4				210227.4				210227.4				210227.4
		[2]	321544.8	-111465.3	-147.9	210227.4	317075.4	-113433.1	-6585.2	210227.4	257363.5	-50137.9	-3001.9	210227.4	699105.9	-480755.1	8123.4	210227.4
		[3]	579792.4	-369712.9	-147.9	210227.4	836312.8	-632670.6	-6585.2	210227.4	907051.0	-699825.4	-3001.9	210227.4	1622686.5	-1404335.8	8123.4	210227.4
		[4]	322829.3	-111465.3	1172.3	210191.7	319166.1	-113433.1	-4455.4	210188.4	262226.4	-50137.9	1899.7	210188.8	699838.1	-480755.1	8891.6	210191.5
		[5]	560744.0	-346689.5	3864.0	210190.6	806701.9	-595507.8	1005.6	210188.5	869538.1	-649015.8	10332.9	210189.3	1556882.0	-1325204.4	21486.0	210191.7
	Internal R&D	[1]				85254.9				85254.9				85254.9				85254.9
		[2]	-21882.5	106687.8	-449.7	85254.9	76498.2	8417.4	-339.3	85254.9	76745.7	9278.1	768.9	85254.9	83825.8	4615.6	3186.5	85254.9
		[3]	215938.1	-131132.9	-449.7	85254.9	476822.0	-391906.4	-339.3	85254.9	526025.6	-440001.8	768.9	85254.9	808295.9	-719854.5	3186.5	85254.9
		[4]	-18851.7	106687.8	2589.1	85247.0	80033.6	8417.4	3207.1	85243.9	81925.8	9278.1	5959.3	85244.6	86363.9	4615.6	5732.8	85246.7
		[5]	202543.5	-112105.4	5193.4	85244.7	454193.5	-361333.9	7615.6	85244.0	500731.8	-403272.1	12215.0	85244.7	768595.6	-666706.9	16642.8	85246.0
	External R&D	[1]				43571.4				43571.4				43571.4				43571.4
		[2]	214291.0	-170768.5	-48.8	43571.4	266426.9	-223081.9	-226.4	43571.4	234632.4	-191445.0	-384.0	43571.4	398763.8	-355143.9	48.5	43571.4
		[3]	233369.0	-189846.4	-48.8	43571.4	312577.3	-269232.3	-226.4	43571.4	304077.7	-260890.3	-384.0	43571.4	487814.4	-444194.5	48.5	43571.4
		[4]	214361.9	-170768.5	25.2	43568.3	266711.8	-223081.9	62.8	43567.1	235739.4	-191445.0	727.2	43567.1	397758.0	-355143.9	-953.4	43567.4
		[5]	231258.3	-187471.5	218.6	43568.2	309128.9	-265014.9	546.8	43567.2	299538.0	-254343.3	1627.5	43567.2	481707.7	-437836.7	303.6	43567.4
	Total R&D per Employee	[1]				534.1				534.1				534.1				534.1
		[2]	3776.5	-3241.2	1.3	534.1	667.9	-176.3	-42.5	534.1	383.8	261.8	111.5	534.1	4888.7	-4106.8	247.8	534.1
		[3]	5446.4	-4911.1	1.3	534.1	6269.7	-5778.1	-42.5	534.1	9099.8	-8454.2	111.5	534.1	16749.7	-15967.8	247.8	534.1
		[4]	3829.1	-3241.2	54.9	533.0	758.9	-176.3	49.5	533.0	443.6	261.8	172.3	533.0	4980.6	-4106.8	340.7	533.1
		[5]	5240.2	-4642.6	64.6	533.0	5887.6	-5271.5	83.0	533.0	8575.9	-7815.1	227.8	533.0	15946.1	-14996.5	416.6	533.1

List of approach
[1] Traditional DID
[2] Linear DID with Interferences, complete model
[3] Linear DID with Interferences, alternative specification without control for $D_j D$
[4] Multilevel DID with interferences, complete model with inclusion of random effects at provincial and regional level
[5] Multilevel DID with interferences, alternative specification (No $D_j D$) with inclusion of random effects at provincial and regional level

The inclusion or not of a treated unit in the neighbourhood of the others is calculated by different cut-off distances: 40 km, 50 km, 75 km, 100 km

variables, with the exception of Total R&D per employee. These results provides evidence on the additionality on R&D expenses. In other words, short term investments on R&D activities are fostered by public policies. Notwithstanding, the novel SH-DID approach implemented in models 2-5 allows to analyse the possible occurrence of spillover effects in R&D activities (i.e. the impact of both own and neighbours' state of treatment).

Considering spatial interactions between units, we observe significant and positive direct effects, particularly in relation to total and external R&D expenses (models 2 and 4). Direct effect is bigger than total impact, suggesting the presence of negative externalities. This is confirmed by negative and meaningful AITET on all variables. Moreover, we demonstrate the spatial limited extent of the spillover effects and the downfall of spatial interferences for high distances. In way of example, external R&D exhibits a wider direct effect for bigger distances. Conversely, indirect effects are characterised by an inverse relation with distances. However, our analysis does not produce evidence of spillover effects on control units (i.e. the impact of having neighbours treated), even if, on the whole, we can observe positive and not significant effects.

In summary, having neighbours treated provides a small improvement on R&D expenses of the control units, while treated units do not have benefits from having treated neighbours. Furthermore, negative spillover effects increase with distances. Negative indirect effects in presence of interferences between units can be, at least partially, explained in terms of job market. In fact, the benefits of sharing information and knowledge in a highly concentrated market can be counterbalanced by a greater competition on skilled workers with detrimental effects on R&D expenditures. In this sense, it is interesting to underline the presence of significant and positive spillovers on Internal R&D. In other words, treated firms implementing R&D activities with own personnel and equipment maximize spatial spillover (i.e. this firms do not match with the detrimental effects of an increase in the demand of skilled workers).

Models 3 and 5 underline the estimation bias if we erroneously omit the check for heterogeneity due to the interaction between own and neighbours state of treatment. The bias of the estimates

Table 5: Results

		OUTCOME									
		Total R&D					Internal R&D				
		[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
40	Dt	210227.4***	321544.8**	579792.4***	322829.3**	560744***	85254.9**	-21882.5	215938.1***	-18851.7	202543.5***
		[69328.8]	[131220.4]	[105588.4]	[128998.1]	[104315.1]	[38792.1]	[73382.2]	[59163.6]	[71665.9]	[58101.0]
	Djt		-2453.3	-2453.3	19440.3	64078.3		-7456.9	-7456.9	42937.0	86124.6
			[265623.6]	[265900.2]	[295391.25]	[295376.5]		[148544.2]	[148990.0]	[165973]	[166258.9]
	DjDt		-1740489.6	-5778613***	-1762383.3	-5485135.5***		1675694.8*	-2043020.6***	1625300.9Âř	-1839076.5***
			[1746459.7]	[1250436.3]	[1718881.4]	[1241905.4]		[976669.9]	[700648]	[955053.7]	[692208.7]
50	Dt	210227.4***	317075.4**	836312.8***	319166.1**	806701.9***	85254.9**	76498.2	476822.0***	80033.6	454193.5***
		[69328.8]	[151726.5]	[118948.6]	[149330.7]	[117735.6]	[38792.1]	[84566.9]	[66487.2]	[82731.1]	[65458.1]
	Djt		-109582.7	-109582.7	-74142.0	16734.4		-5646.5	-5646.5	53368.6	126729.8
			[320069.4]	[321043.7]	[364895.0]	[365632.1]		[178395.1]	[179449.8]	[204916.9]	[205892.3]
	DjDt		-1565786.5	-9234751***	-1601227.3	-8812187***		129968.4	-5782680.5***	70953.3	-5463511***
			[2002662.7]	[1438433.5]	[1974272.8]	[1430472.5]		[1116212.3]	[804023.3]	[1093964.5]	[795889.9]
75	Dt	210227.4***	257363.5	907051***	262226.4	869538.1***	85254.9**	76745.7	526025.6***	81925.8	500731.8***
		[69328.8]	[183465.1]	[139944.8]	[180659.0]	[138477.5]	[38792.1]	[102389.3]	[78230.6]	[100198.5]	[76977.5]
	Djt		-50221.2	-50221.2	31781.5	172869.0		12864.5	12864.5	99699.4	204356.4
			[384978.9]	[386136.5]	[453418.7]	[453941.7]		[214851.4]	[215854.5]	[255562.3]	[256220.7]
	DjDt		-694491.4	-10344477***	-776494.1	-9812878***		124945.8	-6548331***	38110.9	-6194267***
			[2531868]	[1816324.1]	[2497161.5]	[1802749.3]		[1413000.4]	[1015344.9]	[1385237]	[1002568.2]
100	Dt	210227.4***	699105.9***	1622686.5***	699838.1***	1556882***	85254.9**	83825.8	808295.9***	86363.9	768595.6***
		[69328.8]	[229717.5]	[171128.2]	[226349.4]	[169816.5]	[38792.1]	[128248.3]	[95886.5]	[125537.1]	[94613.3]
	Djt		136358.7	136358.7	149253.5	360663.2		53489.2	53489.2	96230.6	279364.9
			[438059.3]	[439662.5]	[529803.9]	[530607.7]		[244562.8]	[246351.5]	[299238.6]	[300592.4]
	DjDt		-7258381.5**	-20940528***	-7271276**	-19992560***		14887.8	-10717588***	-27853.6	-10156122***
			[3254798]	[2330740.3]	[3211352]	[2317760.5]		[1817111.5]	1305959.0	[1781330.9]	[1291727.1]

		OUTCOME									
		External R&D					Total R&D per Employee				
		[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
40	Dt	43571.4**	214291***	233369.0***	214361.9***	231258.3***	534.10	3776.5	5446.4**	3829.1	5240.2**
		[18674.5]	[35163.8]	[28265.1]	[34677.0]	[28017]	[1698.1]	[3222.7]	[2590.5]	[3211.6]	[2586.5]
	Djt		-808.9	-808.9	417.5	3625.6		21.0	21.0	911.1	1071.0
			[71180.5]	[71179.3]	[79494.9]		[6523.6]	[6523.5]	[6905.1]	[6901.8]	
	DjDt		-2669435.3***	-2967750***	-2670661.8***	-2935048.8***		-50701.7	-76814**	-51591.8	-73665.8**
			[468008]	[334731.4]	[462070.9]	[333574.3]		[42892.5]	30677.6	[42767.0]	[30692.2]
50	Dt	43571.4**	266426.9***	312577.3***	266711.8***	309128.9***	534.10	667.9	6269.7**	758.9	5887.6**
		[18674.5]	[40698]	[31816.7]	[40177.8]	[31595.9]	[1698.1]	[3740.6]	[2925.1]	[3729.5]	[2921.7]
	Djt		-3767.2	-3767.2	1044.6	9098.7		-707.1	-707.1	824.5	1381.1
			[85852.9]	[85873.7]	[98263.6]	[98213.7]		[7890.9]	[7894.8]	[8440.9]	[8447.4]
	DjDt		-3291078.3***	-3972703.5***	-3295890***	-3923281.3***		-1896.8	-84634.2**	-3428.5	-79240**
			[537178.9]	[384756.3]	[531189.8]	[383906.6]		[49373.2]	[35372.8]	[49262.2]	[35385.9]
75	Dt	43571.4**	234632.4***	304077.7***	235739.4***	299538***	534.10	383.8	9099.8***	443.6	8575.9**
		[18674.5]	[49384.6]	[37571.5]	[48774.3]	[37297.5]	[1698.1]	[4515.7]	[3437]	[4503.4]	[3433.8]
	Djt		-6423.9	-6423.9	12166.8	27227.5		1865.1	1865.1	2882.8	3810.5
			[103627.5]	[103667.6]	[122594.3]	[122463]		[9475.5]	[9483.3]	[10270.5]	[10280.9]
	DjDt		-2837161.3***	-3868651.3***	-2855752***	-3805058.3***		2023.2	-127438.2***	1005.5	-119890.5***
			[681521]	[487635.6]	[674194]	[485573.7]		[62317.2]	[44608.0]	[62189.9]	[44613.6]
100	Dt	43571.4**	398763.8***	487814.4***	397758.0***	481707.7***	534.10	4888.7	16749.7***	4980.6	15946.1**
		[18674.5]	[61876.7]	[45944.3]	[61120.9]	[45726.0]	[1698.1]	[5680.1]	[4219.8]	[5665.5]	[4221.6]
	Djt		814.3	814.3	-16002.9	5095.8		4159.4	4159.4	5718.6	6992.3
			[117995.5]	[118040.2]	[143367.4]	[143141.3]		[10831.6]	[10841.5]	[11880.0]	[11906.3]
	DjDt		-5262002.5***	-6581219.5***	-5245185.5***	-6491314.5***		-64998.7	-240710.4***	-66557.8	-229153.4***
			[876711.5]	[625754.9]	[867173.3]	[624117.1]		[80479.2]	[57472.9]	[80317.3]	[57541.9]

Significance Level: * 0.01, ** 0.05, * 0.1**
Standard Errors in Square Bracket

List of approach
[1] Traditional DID
[2] Linear DID with Interferences, complete model
[3] Linear DID with Interferences, alternative specification without control for D_jD
[4] Multilevel DID with interferences, complete model with inclusion of random effects at provincial and regional level
[5] Multilevel DID with interferences, alternative specification (No D_jD) with inclusion of random effects at provincial and regional level

The inclusion or not of a treated unit in the neighbourhood of the others are calculated by different cut-off distances: 40 km, 50 km, 75 km, 100 km

appear clear in particular with reference to direct and indirect effects on the treated. Nevertheless, the results of the "restricted" model are in line with the ones of the complete model for both direct and indirect effects. As indicated in preceding sections, the results of the novel SH-DID model can be easily recombined in the ATE. Table 4 resumes the decomposition process of the ATE, highlighting the average intensity of both direct and indirect effects. This table gives a clear overview on the extension of treatment effects. The analysis of the paths followed by the decomposition process open up two distinct considerations.
On the one hand, the complete models (i.e. 2 and 4) shows equal estimates of the AITET, but differentiated results for ADTE and AITENT. As explained above, this is mainly due to the different estimation procedures. Indeed, linear model does not correctly distinguish between different indirect effects, even if it is able to catch unbiased ATE estimates. Instead, hierarchical model is a good approximation of both total, direct and indirect effects and, on the whole, the SH-DID model produces unbiased and more efficient estimates. On the other hand, the decomposition of the ATE shows a strong and positive direct additionality of the policies, while the results on the indirect effects are ambiguous. Indeed, the estimates shows negative and significant spillovers on the treated, while positive a negligible effects on the controls. Furthermore, both direct and indirect effects are influenced by the distance. The paths followed by treatment effects for different cut-off distances have a dual implication on the results. While ADTE increases with distance, we observe a decline of the AITET on treated and a substantial improvement of the AITENT.

7 Conclusions

In this paper we propose a novel approach to evaluate spillover effects in causal analysis. We modify a traditional Diff-in-Diff approach to include directly the presence of spatial interferences. The identification problems related to the inclusion of interferences are addressed by testing three distinct approaches: linear, spatial and spatial-hierarchical. Montecarlo Simulation demonstrate how the spatial hierarchical Diff-in-Diff (SH-DID) provides unbiased estimates of direct and indirect effects and, consequently, of the ATE.
In the second part of the work, we test our novel approach to the case of R&D expenditures for Italian firms. effectiveness of public policies in Italy to foster innovation and R&D processes. The results show significant and positive ATE on total, internal and external R&D expenses. Considering that this paper focuses only on short-term effects, the choice of R&D expenditures to evaluate public policies effectiveness is preferable. In fact, it seems reasonable to expect a longer temporal lag between innovation production and economic and financial benefits on the activities of the firms.
However, this in-depth analysis requires the availability of additional data referred to a wider time window. In this sense, the provision of empirical evidence on the existence of a relation between

the significant improvement on R&D expenditures and a strengthening of innovation and economic performances of the firms will be the subject of future studies.

Notwithstanding, the main novelty of this paper consists in the development of a methodology able to include spatial interferences in causal analysis. This approach allows to decompose the ATE in both direct and indirect treatment effects. On the basis of Hudgens and Halloran (2012), we refer to direct effect as the response to the treatment, while the indirect impact is the reply to interferences. However, the definition of interactions between units can be ambiguous and potentially addressed in different ways. To overcome the difficulties on the extent and the role of interferences we include in our analysis only their "spatial" dimension.

More in detail, our methodological approach consists in the inclusion, in the regression model of a Diff-in-Diff estimator, of a variable indicating the state of treatment of the neighbours and the consequent interaction with own state of treatment and time. Moreover, under this assumption we are able to distinguish between indirect effects on treated and controls. This intuition is related to the idea that neighbours' treatment can stimulate competitiveness on innovation and labour market. This can generates both centrifugal and centripetal forces.

In fact, on the one hand we can expect the formation of stable network of firms in developing R&D activities. Furthermore, the increase on competitiveness collides with the requirement of more specialized human capital and the subsequent additional rivalry on labour market. Differentiated effects on treated and controls allows to take into account the trade-off between policy effectiveness and the improvement of local competitiveness.

This point is of substantial interest for policy maker. Indeed, rethinking the role of interactions between units as an additional instrument to foster innovation and growth, can lead to a substantial refinement of public policies. From this perspective, the introduction of spatial interferences in causal analysis allows the development of "smart" policies able to maximize the formation of spillover effects taking into account the spatial distribution of the units.

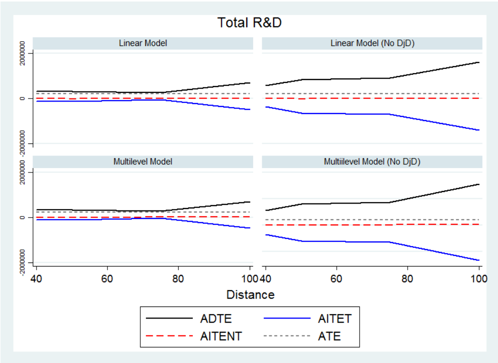
The estimates exhibit an higher intensity of the direct effects in comparison of the ATE, while we observe negative and significant AITET and positive, but negligible, AITENT for all the variables. This result has a twofold relevance. Firstly, the strengthening of direct policy effectiveness implies a substantial improvement of firm capabilities to innovate in the local market, even in absence of interferences.

Conversely, the negative AITET demonstrates the occurrence of congestion effect on labour market that can have detrimental impacts on the additionality of the policies. These two intuitions underline the relation between spatial distribution of the treatment and the objectives of the policies. In fact, in the case in which policies aim to maximize the benefit of being treated it will be preferable a dispersed distribution of the treatment (i.e. 0 or low level of spatial interactions). While, in the case in which the Public Authority seeks to optimize overall territorial competitiveness, it is requested low-medium level of interactions[10]. Furthermore, this work demonstrates the role of

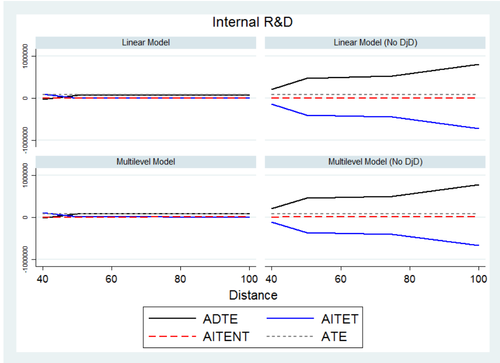
[10]We can imagine two different examples to resume these assumption. On one hand, we can think to policies devoted to the formation of new firms. In this perspective, the aim of such instruments is necessarily the maximization of the additional benefits of being subsidized. On the other hand, we imagine policies designed to foster the growth in

distance in estimating the spatial extension of both direct and indirect effects.

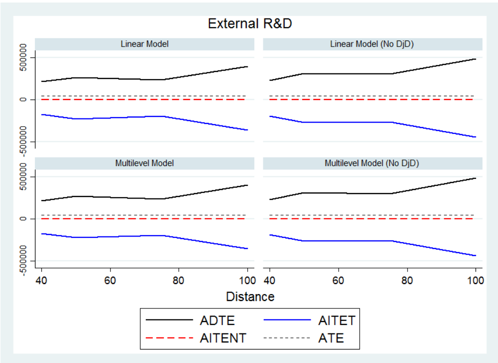
Figure 5: Treatment effects dynamics in function of the distances



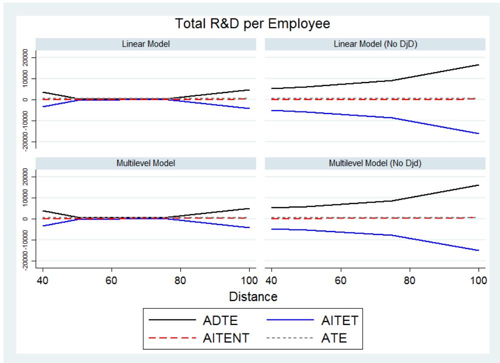
(a)



(b)



(c)



(d)

Note: Figure shows the impact of the distances in the evolution of direct and indirect treatment effects. In detail, panel (a) represents the Total R&D, panel (b) the internal R&D, panel (c) the external R&D, panel (d) the expenses per employee.

Figure 5 resumes the behaviour of treatment effects over space. Focusing on ADTE trend, we observe a stable path moving from short to medium distances, i.e. between 40 and 75 km. However, the direct effect becomes bigger for a cut-off distance equal to 100 km. Conversely, AITET exhibit a similar, even if diverging, path. More in detail, moving the cut-off distance from 40 to 75 km entail limited variations, while AITET significantly worsens over longer distances. Lastly, indirect effects on controls do not present significant variations when cut-off distance changes from 40 to 100 km.

These results are in line with our expectation. They demonstrate that direct effect assumes a primary role when the strength of the interactions between units is weakened. However, the distribution of treatment effects over space suggests the possible occurrence of non-linear interferences. The determination of the appropriate functional form to analyse spatial interferences goes beyond the objectives of this paper, even if, to fully understand the role of interactions between units in causal analysis, can be an interesting further step of our research.

undeveloped areas. It seems reasonable to assume that this instrument aims to maximize the spillover effects.

To conclude, this paper proposes a suitable empirical framework able to evaluate total, direct and indirect policy effectiveness. Furthermore our novel approach could constitute a turning point of the definition of political priority and efficiency of EU policies, taking into account the relations between spatial distribution of the firms, knowledge spillovers and local competitiveness.

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