Evaluating direct and indirect treatment effects in Italian RD expenditures

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Evaluating direct and indirect treatment effects in Italian R&D expenditures

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Abstract

During the last decades SUTVA has represented the "gold standard" for the identification and evaluation of causal effects. However, the presence of interferences in causal analysis requires a substantial review of the SUTVA hypothesis. This paper proposes a framework for causal inference in presence of spatial interactions within a new spatial hierarchical Difference-in-Differences model (SH-DID). The novel approach decomposes the ATE, allowing the identification of direct (ADTE) and indirect treatment effects. In addition, our approach permits the identification of different indirect causal impact both on treated (AITET) and on controls (AITENT). The performances of the SH-DID are evaluated by a Montecarlo Simulation. The results confirm how omitting the presence of interferences produces biased parameters of direct and indirect effects, even though the estimates of the ATE in the traditional model are correct. Conversely, the 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. The estimates show the additionality 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 the treated.

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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. It follows an economic geography school of thought which recognises the presence of heterogeneity between regions (von Tunzelmann, 2009), the influence of different types of innovation on competitiveness (Jensen et al., 2007) and the ways in which different institutional configurations can promote distinct economic activities.

Efficient Smart specialization policies rely on the concepts of embeddedness and connectedness. Camagni and Capello (2013) suggest the implementation of ad-hoc local policies to adequately support regional innovation systems. This intuition 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.

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 point of view, the development of sectoral and spatial linkages becomes essential to foster knowledge spillovers and, in wider term, innovation. The growing interest on spillover effects is not limited to government viewpoint. In fact, the awareness and estimation of the spillovers becomes a central pillar in 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. The identification of the causal effects typically relies on the validity of the Stable Unit Treatment Value Assumption, or SUTVA[3](Rubin, 1980). This hypothesis imposes the absence of interferences between units (Cox, 1959). For this reason, in the traditional experimental approach, 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 a correct identification and

[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, 2004); Anselin et al. (1997); Breschi and Lissoni (2001); Porter (1998); Camagni (1991); Fritsch and Slavtchev (2011).

[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).

estimation of the indirect treatment effects.
Moreover, the development place-based policies pointed towards the formation of spatial and social linkages between economic agents and the requirement of methodological methods able to evaluate the effects of the 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 works consists in the evaluation of both direct and indirect (i.e. spillovers) treatment effects on Italian R&D expenditures. The estimates are implemented by the modified Diff-in-Diff approach proposed in Di Gennaro and Pellegrini (2016b). This approach directly includes the presence of spatial interferences in the regression model. In this way, the novel approach allows to estimate direct and indirect effects by decomposing the ATE.

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), studying a setting with interactions between units, define the *”direct effect”* as the response of the agents to the treatment, while the *”indirect effect”* are the response to the interferences. Under this perspective, the knowledge of the indirect effects has a twofold impact on causal analysis. On one hand, it can ensure unbiased estimates of treatment effects by decomposing the total impact of the policies in its direct and indirect component. Furthermore, indirect effects play a central role in the case in which treatment induces interaction.
This intuition, been based on the identification of the interferences between units, produces a meaningful pattern between the two previous questions. Rosenbaum (2012) argues that interferences can be *" unlimited in extent and impossible to specify in form"* making their definition generally intractable. Notwithstanding, it is possible to consider the interactions by a function of proximity between units. Appropriate measure of proximity can be: geographical distance, nodal distance in a known social network, metrics of social or economical distance (Cerulli et al., 2014; Hong and Raudenbush, 2012).
Manski observes that the presence of interferences makes not possible to distinguish between endogenous, exogenous and correlated effects. This assumption is resumed in the so-called *”Reflection Problem”* (Manski, 1993, 2000, 2013). Notwithstanding, Corrado and Fingleton (2012) and Gibbons et al. (2014) demonstrate that hierarchical and spatial econometrics approaches enable to

[4]See Zúñiga-Vicente et al. (2014) and Becker (2015) for recent survey on policy evaluation studies. The relevance of this theme for the Italian case is remarked by Caloffi et al. (2016).

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 (Verbitsky-Savitz and Raudenbush, 2012; Feser, 2013; Gibbons et al., 2014).

Verbitsky-Savitz and Raudenbush (2012) underline as the no-interference assumption is likely to be violated in spatial settings because of various spillover, diffusion and displacement effects. The aforementioned authors develop a framework based on a generalized linear model with spatially auto-correlated random effects. Their approach defines appropriate causal effects by the inclusion of a function considering treatment assignments of all the units in the potential outcome.

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) propose a methodology to 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, mostly on the labour market.

Cerqua and Pellegrini (2014) analysing a capital subsidy policy estimate positive effects on subsidised firms in terms of investment, turnover, and employment. However, employment growth is in part determined by the detrimental effect on affected untreated firms located in the proximity of one or more treated firms belonging to the same sector.

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.

Di Gennaro and Pellegrini (2016a) identify the presence of spillover effects by a comparison between treated and controls on the basis of geographical localization and market concentration. However, this approach allows to estimate spillover effects only for the unsubsidised.

In this paper we identify and estimates the indirect effects following an alternative approach developed by Di Gennaro and Pellegrini (2016b). 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 Spatial Hierarchical Diff-in-Diff

The idea behind the definition of a novel framework relies on the "traditional" Potential Outcome Model.

$$y_i = D_i y^1 + (1 - D_i) y^0 = \begin{cases} y^1 & \text{if } D = 1 \\ y^0 & \text{if } D = 0 \end{cases} \tag{1}$$

where D indicates the state of treatment. Rosenbaum (2012) argues that in presence of interferences the number of potential outcome is not equal to 2. In detail, it depends on the sample size and the number of treated units. In this way, the identification of the "traditional" potential outcome in presence of interferences becomes intractable. However, the identification problem can be addressed by imposing a restriction on the extension of the interferences. In this paper we impose a spatial restriction on the extension of the interactions by proposing a proximity function based on the state of treatment of the neighbours.

We still assume the validity of the potential outcome framework, while the presence of interferences between units make possible the decomposition of the overall causal impact in direct and indirect effects. Our approach is built on a different version of the POM (eq. 2) which corresponds to the "traditional" potential outcome to whom we add and subtract the equation in 1 multiplied by D_j. This term, derived applying a spatial lag of the treatment variable, represents the neighbours' state of treatment:

$$y = Dy^1 + (1 - D)y^0 + D_j(Dy^1 + (1 - D)y^0) - D_j(Dy^1 + (1 - D)y^0) \tag{2}$$

Equation 2 can be rearranged and write as:

$$y = \underbrace{(1 - D_j)(Dy^1 + (1 - D)y^0)}_{\text{Effect without interactions}} + \underbrace{D_j(Dy^1 + (1 - D)y^0)}_{\text{Effect of the interactions}} \tag{3}$$

Equation 3 permits to distinguish between direct and indirect effects. In detail, the first term in 3 represents the direct effect (i.e. the total effect purified by the impact of the interferences), while the latter constitutes the indirect effect. Note that the indirect effects are determined by the first order's neighbour[5]. In this way, we can decompose the ATE as the sum of direct and indirect effects, as reported in 4.

$$ATE = ADTE + AITE = (1 - D_j)ATE + D_j ATE \tag{4}$$

Translating this idea in a "traditional" Difference-in-Difference method allows to obtain consistent

[5]Different typologies of neighbours can be considered on the basis of the adopted spatial framework.

estimation of both direct and indirect treatment effects. As is known, the "traditional" DID model allows to evaluate the ATE as the parameter β_3 of the following equation:

$$Y = \beta_0 + \beta_1 D + \beta_2 T + \beta_3 DT \tag{5}$$

or expressed in terms of expectations as in Equation 6:

$$\begin{aligned} a_S &= E[Y|D=1, T=1] = \beta_0 + \beta_1 + \beta_2 + \beta_3 \\ b_S &= E[Y|D=1, T=0] = \beta_0 + \beta_1 \\ c_S &= E[Y|D=0, T=1] = \beta_0 + \beta_2 \\ d_S &= E[Y|D=0, T=0] = \beta_0 \\ ATE &= (a_S - b_S) - (c_S - d_S) = \beta_3 \end{aligned} \tag{6}$$

The formulations in 5 and 6 provide correct estimates of the treatment effect, even if it rules out the presence of inferences between units. In this sense, a substantial modification of the Diff-in-Diffs approach is required. The objective of this paper is to adapt the intuition in 2 in the regression model expressed in 5.

In other words we include an additional part in the "standard" DID estimator multiplied by the state of treatment of the neighbours units in order to model the presence of interactions. This allows to obtain the specification in 7:

$$Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j D + \beta_6 D_j Dt \tag{7}$$

Using the specification in 7 we are able to estimate simultaneously both total, direct and indirect causal effects. Applying the "standard" Diff-in-Diffs approach to 7 provides unbiased estimates of the ATE. However, in this case, the ATE is a composite parameter. The novel approach makes possible a decomposition of the ATE in order to identify and isolate the quota of impact attributable to the interferences. In this way the formulation of the ATE becomes:

$$ATE = \beta_3 + \beta_4(\overline{D_j^1} - \overline{D_j^0}) + \beta_6 \overline{D_j^1} \tag{8}$$

The term $\overline{D_j^1}$ (resp. $\overline{D_j^0}$) indicates the average share of treated neighbours for subsidized (resp. control) units. The ATE in 8 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 treatment induces interactions between units, i.e. in the neighbourhood of the considered unit is located at least one treated unit. From 7 we derive the impact of direct and indirect causal effects:

$$\begin{aligned}
&a = E[Y|D=1, t=1, D_j \neq 0] = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4\overline{D_j^1} + \beta_5\overline{D_j^1} + \beta_6\overline{D_j^1} \\
&b = E[Y|D=1, t=1, D_j = 0] = \beta_0 + \beta_1 + \beta_2 + \beta_3 \\
&c = E[Y|D=1, t=0, D_j \neq 0] = \beta_0 + \beta_1 + \beta_5\overline{D_j^1} \\
&d = E[Y|D=1, t=0, D_j = 0] = \beta_0 + \beta_1 \\
&e = E[Y|D=0, t=1, D_j \neq 0] = \beta_0 + \beta_2 + \beta_4\overline{D_j^0} \\
&f = E[Y|D=0, t=1, D_j = 0] = \beta_0 + \beta_2 \\
&g = E[Y|D=0, t=0, D_j \neq 0] = \beta_0 \\
&h = E[Y|D=0, t=0, D_j = 0] = \beta_0
\end{aligned} \tag{9}$$

The direct effect (ADTE) is estimated by a double differences 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 10:

$$ADTE = b - d - f + h = \beta_3 \tag{10}$$

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, assuming own state of treatment constant.

$$AITET = a - c - b + d = \beta_4\overline{D_j^1} + \beta_6\overline{D_j^1} \tag{11}$$

$$AITENT = e - g - f + h = \beta_4\overline{D_j^0} \tag{12}$$

Formulations in 11 and 12 represent respectively the AITET (Average Indirect Treatment Effects on the Treated) and the AITENT (Average Indirect Treatment Effects on the Controls) [6].

4 Empirical Strategy

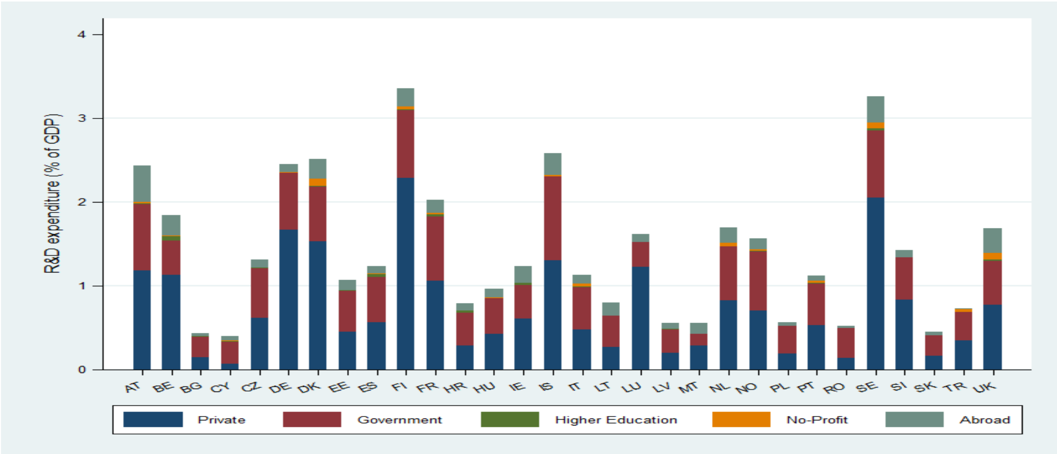
4.1 Public Policies

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 1 remarks the European lack of investments in innovation. In this context, Italy exhibits

[6] An in-depth analysis of the SH-DID model is in Di Gennaro and Pellegrini (2016b)

Figure 1: 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.

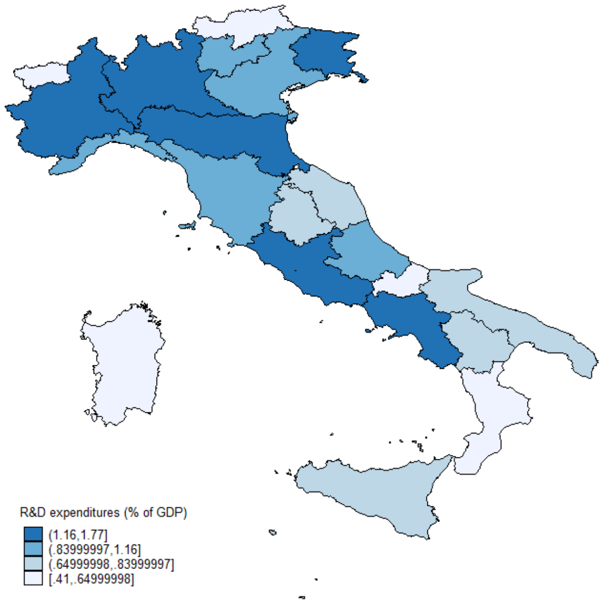
R&D expenditures below European average, regardless of the source of funds. More in detail, in 2007 Italy invests the 0.61 % of the GDP in private R&D, while the 0.52 % of the GDP is devoted to public expenditures. The inadequate effort on R&D appears evidently comparing Italian and European averages. 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 comparative analysis emphasises the shortage of private R&D expenditures. This discrepancy is meaningful to determine the opportunity for Public intervention to obviate private underinvestment. Furthermore, R&D expenditures are not uniformly distributed across Italian Regions. Figure 2 underlines a greater propensity to R&D processes in Northern Regions (with the exception of Aosta Valley and Trentino South-Tirol), while Southern and Insular regions exhibit, on average, lower level of R&D expenditures. The development gap between North and South does not affect only R&D expenses but can be considered one of the major weakness of Italian economic system . Moreover, structural differences can also be found in regional economic accounts and employment rates (MISE, 2015).

The lack of R&D investments and the territorial development gap has required a strong intervention both at European and National level. During the 2007-2013 programming period, 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 [7].

[7]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

Figure 2: Italian R&D Expenditures in % of the GDP



Source: Eurostat
Note: This figure shows Italian Regional R&D expenditures for the year 2007. It demonstrates a greater propensity to R&D process for the Central and Northern Regions.

Table 1: 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

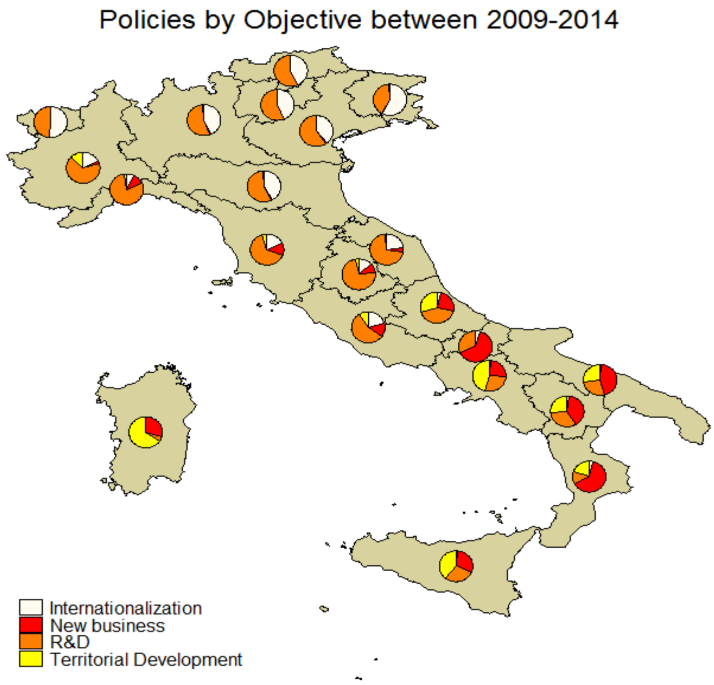
Source: EU Commission
Note: Figures have been rounded up.
*Each Territorial Cooperation programme includes a minimum of 15% co-financing from each participating Member State.

Table 1 resumes the total amount of public funding in Italy between 2007-2013. The country-wide 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.

The main objective in programming period 2007-13 is the reinforcement of Southern regions to catch up with the European average in terms of GDP per capita. 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.

Figure 3: Objective of public policies



Note: Figure 3 shows the different objectives of the public policies distinguished by Region.

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.

Figure 3, analysing the different objectives followed by the policies, remarks the structural differences between Northern and Southern Regions. The firsts develop policies able to promote internationalization and R&D, while the main objectives in Convergence Regions are the growth of territorial competitiveness and the support to new businesses. The different territorial objectives reflect the distinct state of advancement of technological processes between North and South.

4.2 Data

In this work we provide evidence on direct and indirect 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 Community Innovation Survey[8] (CIS): 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. The introduction of indirect effects requires to geolocate companies along Italian territory. Considering the large sample size, 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.

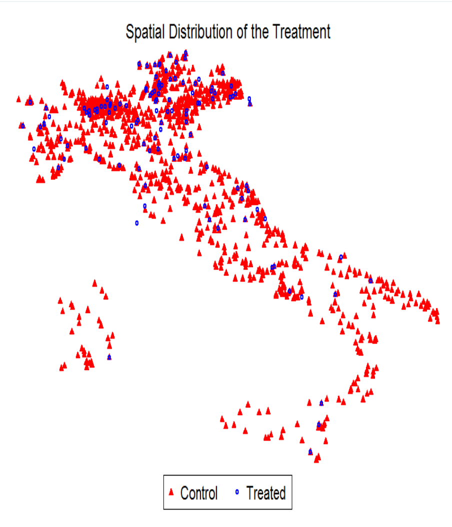
In this way, we are able to include all the incentives provided to the firms in order to avoid the presence of treated units in control group[9]. Conversely, the correct identification of a pre and post treatment period required the exclusion from the sample of all the firms subsidized on 2008 or on both periods. Furthermore, we limit our analysis to SMEs. This decision has a twofold relevance. On one hand, part of the literature underlines a greater additionality of R&D policies on the SMEs sample (see Bronzini and Piselli (2016) inter alia). In addition, this operation allows to control for the presence of structural differences between the treated and control groups due to the presence of

[8]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 by type of enterprises, on the different types of innovation and on various aspects of the development of an innovation, such as the objectives, the sources of information, the public funding, the innovation expenditures, etc. CIS provides statistics broken down by type of innovators, economic activities and size classes (Eurostat).

[9]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.

large enterprises. However, this operation reduces the overall sample size to 2389 SMEs, of which only 145 treated.

Figure 4: Spatial Distribution of the firms



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

Figure 4 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 the case in which there are a limited number of interferences as a consequence of the exposition to neighbours state of treatment.

Table 2: 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)

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.

4.3 Econometric Model

To ensure robust and unbiased estimates of both direct and indirect effects we follow the approach in Di Gennaro and Pellegrini (2016b). The aforementioned authors demonstrate how the linear model is an unbiased estimator only of the ATE. Indeed, the linear approach is not able to adequately distinguish between direct and indirect effects, i.e. linear model does not allow to estimate separately the parameters of the interferences ($D_j t$) and the interaction between own treatment and the share of treated units in the neighbourhood ($D_j D t$).
The introduction of an alternative hierarchical specification, with heterogeneity at municipal level considered in the random effects, is therefore 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 the 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. $Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j Dt$
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. $Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_6 D_j Dt + \epsilon_j$

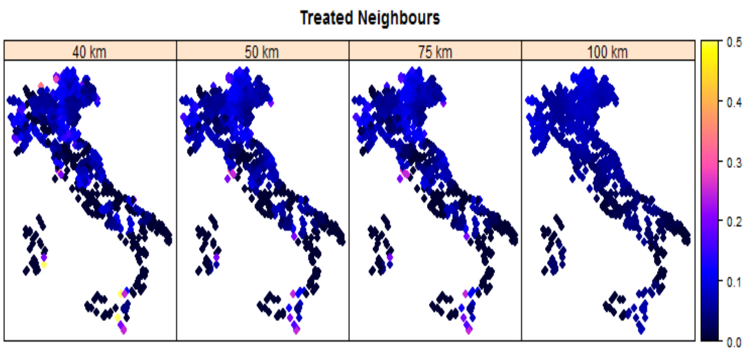
The firsts 3 models are estimated by a linear procedures, while the latter 2 are evaluated by a hierarchical approach. More specifically, model 1 represents the traditional "Diff-in-Diff" approach and it constitutes the benchmark for ATE estimates. The presence of interferences are considered in all the remaining cases.
Furthermore, the difference between linear (resp. hierarchical) models 2 and 3 (resp. 4 and 5) consists of 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) allows 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. Moreover, we are able to identify the spatial

trend followed by direct and indirect causal impacts passing by small to greater distances. This procedure permits to obtain information on the optimal dimension of the spillovers over the space.

5 Results

The objective of this paper is the evaluation of both direct and indirect additionality of Italian innovation policies. As mentioned above, the effectiveness of the treatment is computed using the informations from Community Innovation Surveys. CIS data provide detailed informations on R&D processes, including the benefits from public incentives, R&D expenditures, R&D outputs, data referred to formation and marketing, etc.
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, external R&D and a residual component (Other R&D)[10]. The choice of these variables is adherent for obtaining detailed information on the process of production of innovation and R&D.

Figure 5: 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.

Figure 5 analyse the share of neighbours treated for all the firms included in our analysis along

[10]The Internal R&D includes systematic or occasional activities developed by the firms with own personnel and equipment. The term external R&D is referred to innovation activities implemented by other firms or institution, whereas other R&D is a comprehensive indicator which includes acquisition of equipment, design, formation and training, marketing, etc.

Italian territory. Every panel represent a different cut-off distances. This procedure makes possible an in-depth analysis on the impact of the distance on the quota of neighbours treated. 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 a low share 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[11]. This relation is deepened in the discussion of the results (see table 4).

The discussion of the results consists of a step-by-step analysis. Firstly, we focus on the total impact of the treatment (model 1). The ATE estimated in model 1 constitutes the benchmark for the decomposition process proposed with the alternative Difference in Difference models[12] The estimates demonstrate positive and significant ATE for almost all the outcome 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 the total impact, suggesting the presence of negative externalities. This is confirmed by negative and meaningful AITET on both above-mentioned variables. Moreover, we demonstrate the spatial limited extent of the spillover effects and the downfall of spatial interferences for high distances.

For instance, external R&D exhibits a wider direct effect for bigger distances. Conversely, indirect effects are characterised by an inverse relation with distance. This intuition is confirmed by the results on total R&D expenses. 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. However, treated units do not have benefits from having treated neighbours. Moreover, increasing the level of spatial interferences increase the detrimental effects of having

[11]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 in comparison with the effect on C.

[12]As mentioned above, our approach allows to decompose the ATE in direct and indirect effects. The robustness and correctness of this methodology requires to take into account the unbiased ATE obtained by the "traditional" Diff-in-Diff.

Table 3: 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
	Other R&D	[1]				81401.2				81401.2				81401.2				81401.2
		[2]	129136.3	-47384.6	350.5	81401.2	-25849.7	101231.4	-6019.5	81401.2	-54014.7	132029.0	-3386.8	81401.2	216516.3	-130226.8	4888.3	81401.2
		[3]	130485.3	-48733.6	350.5	81401.2	46913.6	28468.1	-6019.5	81401.2	76947.6	1066.7	-3386.8	81401.2	326576.2	-240286.7	4888.3	81401.2
		[4]	129689.0	-47384.6	916.9	81387.4	-24773.2	101231.4	-4928.8	81387.1	-52150.4	132029.0	-1508.7	81387.3	219294.1	-130226.8	7679.4	81387.9
		[5]	125453.1	-43182.6	883.2	81387.4	39209.0	37747.5	-4430.6	81387.1	66348.2	14532.1	-507.0	81387.4	307179.6	-217357.5	8434.2	81387.9
	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

neighbours treated. The occurrence of negative spillovers 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 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 the preceding section, the results of the novel SH-DID model can be easily recombined in the ATE. Table 3 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

Table 4: Results

		OUTCOME									
		Total R&D					Internal R&D				
		[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
	Dt	210.2***	321.5**	579.8***	322.8**	560.7***	85.3**	-21.9	215.9***	-18.9	202.5***
		[69.3]	[131.2]	[105.6]	[129]	[104.4]	[38.8]	[73.4]	[59.2]	[71.7]	[58.1]
	Djt		-2.5	-2.5	19.4	64.1		-7.5	-7.5	42.9	86.1
40			[265.6]	[265.9]	[295.4]	[295.4]		[148.5]	[148.9]	[166.0]	[166.3]
	DjDt		-1740.5	-5778.6***	-1762.4	-5485.1***		1675.7*	-2043.0***	1625.3*	-1839.1***
			[1746.5]	[1250.4]	[1718.9]	[1241.9]		[976.7]	[700.6]	[955.1]	[692208.7]
	Dt	210.2***	317.0**	836.3***	319.2**	806.8***	85.3**	76.5	476.8***	80.0	454.2***
		[69.3]	[151.7]	[118.9]	[149.3]	[117.7]	[38.8]	[84.6]	[66.5]	[82.7]	[65.5]
	Djt		-109.6	-109.6	-74.1	16.7		-5.6	-5.6	53.4	126729.8
50			[320.1]	[321.0]	[364.9]	[365.6]		[178.4]	[179.4]	[204.9]	[205892.3]
	DjDt		-1565.8	-9234.7***	-1601.2	-8812.2***		130.0	-5782.7***	70.9	-5463.5***
			[2002.7]	[1438.4]	[1974.2]	[1430.4]		[1116.2]	[804.0]	[1094.0]	[795.9]
	Dt	210.3***	257.3	907.1***	262.2	869.6***	85.3**	76.7	526.0***	81.9	500.7***
		[69.3]	[183.5]	[140.0]	[180.7]	[138.5]	[38.8]	[102.4]	[78.2]	[100.2]	[77.0]
	Djt		-50.2	-50.2	31.8	172.9		12.9	12.9	99.7	204.4
75			[385.0]	[386.1]	[453.4]	[453.9]		[214.9]	[215.9]	[255.6]	[256.2]
	DjDt		-694.5	-10344.5***	-776.5	-9812.9***		124.9	-6548.3***	38.1	-6194.2***
			[2531.9]	[1816.3]	[2497.1]	[1802.7]		[1413.0]	[1015.3]	[1385.2]	[1002.6]
	Dt	210.3***	699.1***	1622.7***	699.8***	1556.9***	85.3**	83.8	808.3***	86.4	768.6***
		[69.3]	[229.7]	[171.1]	[226.3]	[169.8]	[38.8]	[128.2]	[95.9]	[125.5]	[94.6]
	Djt		136.4	136.4	149.2	360.1		53.5	53.5	96.2	279.4
100			[438.1]	[439.7]	[529.9]	[530.6]		[244.6]	[246.4]	[299.2]	[300.6]
	DjDt		-7258.4**	-20940.5***	-7271.3**	-19992.6***		14.9	-10717.6***	-27.8	-10156.1***
			[3254.8]	[2330.7]	[3211.3]	[2317.8]		[1817.1]	1306.0	[1781.3]	[1291.7]

		External R&D					Other R&D					Total R&D per Employee				
		[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
	Dt	43.6**	214.3***	233.4***	214.4***	231.3***	81.4**	129.1*	130.5**	129.7*	125.5**	0.5	3.8	5.4**	3.8	5.2**
		[18.7]	[35.2]	[28.3]	[34.7]	[28.0]	[36.5]	[69.4]	[55.8]	[69.0]	[55.6]	[1.7]	[3.2]	[2.6]	[3.2]	[2.6]
	Djt		-0.8	-0.8	0.4	3.6		5.8	5.8	15.2	14.6		0.002	0.002	0.9	1.1
40			[71.2]	[71.2]	[79.5]	[79.5]		[140.4]	[140.4]	[150.1]	[150.0]		[6.5]	[6.5]	[6.9]	[6.9]
	DjDt		-2669.4***	-2967.7***	-2670.7***	-2935.0***		-746.7	-767.8	-756.1	-689.9		-50.7	-76.8**	-51.6	-73.7**
			[468.0]	[334.7]	[462.1]	[333.6]		[923.3]	[660.3]	[919.3]	[660257.1]		[42.9]	[30.7]	[42.8]	[30.7]
	Dt	43.6**	266.4***	312.6***	266.7***	309.1***	81.4**	-25.8	46.9	-24.8	39.2	0.5	0.7	6.3**	0.8	5.9**
		[18.7]	[40.7]	[31.8]	[40.2]	[31.6]	[36.5]	[80.6]	[63.0]	[80.2]	[62.8]	[1.7]	[3.7]	[2.9]	[3.7]	[2.9]
	Djt		-3.8	-3.8	1.0	9.1		-100.2	-100.2	-82.0	-73729.2		-0.7	-0.7	0.8	1.4
50			[85.9]	[85.9]	[98.3]	[98.2]		[169.9]	[169.9]	[184.3]	[184.2]		[7.9]	[7.9]	[8.4]	[8.4]
	DjDt		-3291.1***	-3972.7***	-3295.9***	-3923.3***		1595.3	520.6	1577.2	631.2		-1.9	-84.6**	-3.4	-79.2**
			[537.2]	[384.8]	[531.2]	[383.9]		[1063.1]	[761.4]	[1059.2]	[761.2]		[49.4]	[35.4]	[49.3]	[35.4]
	Dt	43.6**	234.6***	304.1***	235.7***	299.5***	81.4**	-54.0	76.9	-52.2	66.3	0.5	0.4	9.1***	0.4	8.6**
		[18.7]	[49.4]	[37.6]	[48.8]	[37.3]	[36.5]	[97.3]	[74.0]	[96.9]	[73.9]	[1.7]	[4.5]	[3.4]	[4.5]	[3.4]
	Djt		-6.4	-6.4	12.2	27.2		-56.7	-56.7	-25.2	-8.5		1.9	1.9	2.9	3.8
75			[103.6]	[103.7]	[122.6]	[122.5]		[204.1]	[204.2]	[225.2]	[225.1]		[9.5]	[9.5]	[10.3]	[10.3]
	DjDt		-2837.2***	-3868.7***	-2855.8***	-3805.1***		2017.7	72.5	1986.3	224.3		2.0	-127.4***	1.0	-119.9***
			[681.5]	[487.6]	[674.2]	[485.6]		[1342.4]	[960.4]	[1337.7]	[959.9]		[62.3]	[44.6]	[62.2]	[44.6]
	Dt	43.6**	398.8***	487.8***	397.8***	481.7***	81.4**	216.5*	326.6***	219.3*	307.2**	0.5	4.9	16.7***	5.0	15.9**
		[18.7]	[61.9]	[45.9]	[61.1]	[45.7]	[36.5]	[122.4]	[90.9]	[121.9]	[90.8]	[1.7]	[5.7]	[4.2]	[5.7]	[4.2]
	Djt		0.8	0.8	-16.0	5.1		82.1	82.1	128.9	141.6		4.2	4.2	5.7	7.0
100			[118.0]	[118.0]	[143.4]	[143.1]		[233.4]	[233.4]	[261.8]	[261.7]		[10.8]	[10.8]	[11.9]	[11.9]
	DjDt		-5262.0***	-6581.2***	-5245.2***	-6491.3***		-2011.3	-3641.7***	-2058.1	-3361.6***		-65.0	-240.7***	-66.6	-229.2***
			[876.7]	[625.8]	[867.2]	[624.1]		[1734.3]	[1237.5]	[1728.4]	[1238.4]		[80.5]	[57.5]	[80.3]	[57.5]

Significance Level: * 0.01, ** 0.05, * 0.1**
Standard Errors in Square Bracket
N.B. Results and standard errors are express in term of thousands of units.

List of approach
[1] Traditional DID
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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

good approximation of both total, direct and indirect effects and, on the whole, the SH-DID model produces unbiased and more efficient estimates. This conclusion is in line with Di Gennaro and Pellegrini (2016b).
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.
To summarize, the different impact of geographical distance sustains the hypothesis at the basis of this thesis. Omitting the role of interferences in causal analysis do not allows to fully understand the effectiveness of the policies. In other terms, only the inclusion of interferences makes possible to fully analyse and understand the spatial dimension of both direct and indirect effects.

6 Conclusions

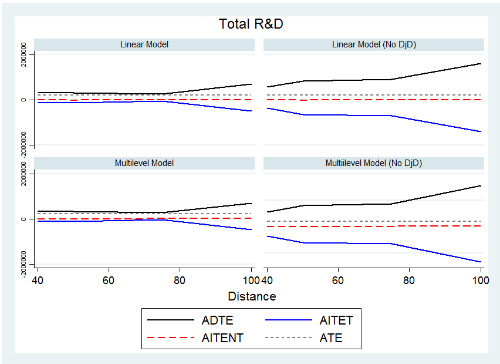
This paper demonstrates the effectiveness of public policies in Italy to foster innovation and R&D processes. The results show significant and positive ATE on total, internal and external R&D expenses. Considering that this paper focuses only on short-term effects, the choice of R&D expenditures to evaluate 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[13].
Furthermore, this chapter demonstrates the role of distance in estimating the spatial extension of both direct and indirect effects.

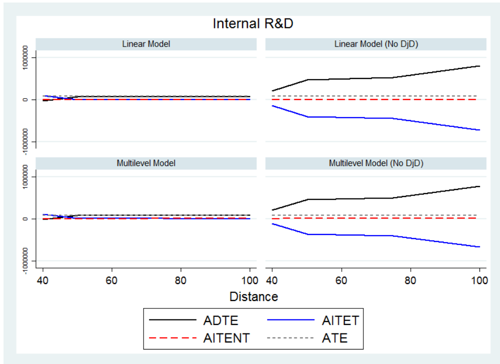
Figure 6 resumes the behaviour of treatment effects over space. Focusing on ADTE trend, we observe a stable path moving from short to medium distances, i.e. between 40 and 75 km. However, the direct effect becomes bigger for a cut-off distance equal to 100 km. Conversely, AITET exhibit a similar, even 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

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

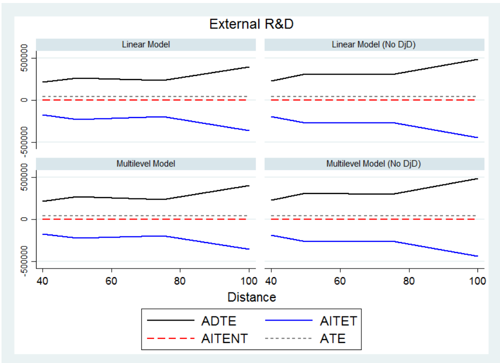
Figure 6: Treatment effects dynamics in function of the distances



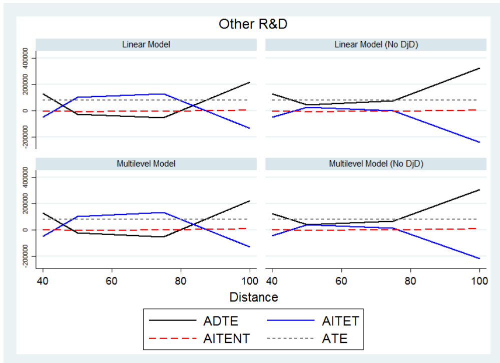
(a)



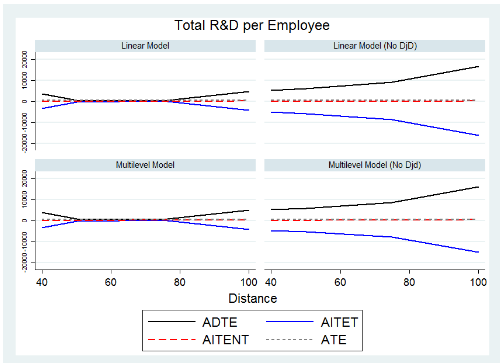
(b)



(c)



(d)



(e)

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) other sources of R&D and panel (e) the expenses per employee.

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.

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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