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POLICY EVALUATION AND INTERFERENCES: AN EMPIRICAL APPLICATION OF A SPATIAL MULTILEVEL DID MODEL

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Abstract

Rubin Causal Model omits the presence of spatial interferences in the definition and estimation of causal impact. In this way, the traditional approach provides unbiased estimates of the ATE, even if makes it not possible to distinguish between direct and indirect (spillover) effects. Following, Di Gennaro and Pellegrini (2016) we provide empirical evidence on the effectiveness of public policies by a modified Diff-in-Diff approach with the inclusion of interactions between units. The interferences are modelled by the state of treatment of the neighbours. This approach allows to recombine the ATE with three different treatment effects: the direct (ADTE) and the indirect on the treated (AITET) and on the controls (AITENT). The estimates shows 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. Moreover, the results are influenced by distances, i.e. increasing the cut-off distance increase, in absolute value, the intensity of the effects.

Keywords: *Causal Inference, Spatial Interferences, Hierarchical Model, Difference in Difference.*

JEL Codes: *C21,R12,R58*

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1 Introduction

In recent years, R&D policies have an increasingly relevant role in stimulating innovation. Moreover, EU Commission aims to foster a *”smart, sustainable and inclusive growth”* developing the ”smart specialization” strategy (Foray et al., 2011). Smart specialization is a ”place-based” policy approach which implies 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 way in which different institutional configurations can promote distinct economic activities.

Smart specialization strategy relies on the concepts of embeddedness and connectedness to develop efficient policies. Camagni and Capello (2013), considering that innovation is rooted into localised and long-term processes[1] and embedded in human capital, interpersonal network and skilled labour markets, suggest the implementation of ad-hoc local policies to appropriately support regional innovation systems. 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 perspective the development of sectoral and spatial linkages become 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 spillovers assumes a primary role in causal analysis and policy evaluation. Nonetheless, the inclusion of indirect effects in the traditional framework is not straightforward and can be considered as one of the main challenges for the researchers, requiring 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, [2](Rubin, 1980). which 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 causal effects from the presence of interferences. However, sustain the validity of the SUTVA does not allow a correct identification and estimation of the indirect treatment effects. The development of place-based policies targeted to the formation of spatial and social linkages between economic agents and the requirement to evaluate the effects of the interferences makes the SUTVA a simplifying, even though unrealistic, assumption. During the last decade, this point assumes a primary role in causal analysis and the investigation of the indirect effects by experimental methods becomes the centre of attention of part of the literature. In the remainder of this paper we provide an in-depth analysis of the literature focuses on the violation of the ”no-interferences” assumption and we evaluate direct and indirect treatment effects on Italian R&D expenditures. The estimates are implemented by the modified Diff-in-Diff approach proposed in Di Gennaro and Pellegrini(2016). This approach directly includes the presence of spatial interferences in the regression model, allowing to decompose the ATE in direct and indirect effects.

[1] 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).

[2] 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).

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[3]. 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, meanwhile they consider the *"indirect effect"* as the response to the interferences. Under this perspective, the interactions between units have a twofold relevance. On the one hand, they make possible the identification of correct total effects of the treatment. Otherwise, include the presence of interferences in a causal framework is essential in the case in which treatment induces interactions. However, the inclusion of interferences is not straightforward. Rosenbaum (2012), highlighting the difficult specification and the potential boundless extent of the interferences, open the possibility of modelling them by appropriate proximity function. Literature proposes different proxy of the interferences, including geographical distance, the nodal distance in a network or the state of treatment of neighbours units.

Manski observes that the presence of interferences makes not possible to distinguish between endogenous, exogenous and correlated effects, proposing the so-called *"Reflection Problem"* to resume the dilemma of the identification of causal effects in such framework (Manski, 1993, 2000, 2013). Notwithstanding, Corrado and Fingleton (2012) and Gibbons et al. (2014) demonstrate that making use of hierarchical modelling and spatial econometrics tools enables to analyse the identification problem related to the inclusion of interactions between units. 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, 2012; 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 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 in the potential outcome of a function which consider treatment assignments of all the units. 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, the employment growth is in part determined to the detrimental effect on affected untreated firms located in the proximity of one or more treated firms belonging to the same sector. Arpino et al. (2013) model interactions as a function of units characteristics, such as geographical distance between firms and firms' size. They show, for the case of small hand-craft firms in Italy, that the additionality of the policy 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 (2016) identify the presence of

[3]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).

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 (2016). This method, modelling the presence of spatial interferences in a Difference in Difference framework, allows to decompose the average treatment effect and estimates separately 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 Empirical Strategy

3.1 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 distant from the 3% objective specified in the Horizon 2020 plan.

INSERT FIGURE 1

Figure 1 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 PIL in private R&D, while the 0.52 % of the PIL is devoted to public expenditures. The inadequate effort on R&D appears evidently considering EU average values equal to 1.17 and 0.66 which, respectively, represent the quota of the PIL devoted to private and public R&D. The comparative analysis emphasises the shortage of private R&D expenditures. This discrepancy is meaningful to determine the opportunity for Public intervention in order to obviate private underinvestment. Furthermore, R&D expenditures are not uniformly distributed across Italian Regions.

INSERT FIGURE 2

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 is not limited to R&D but can be found in both regional economic accounts and employment rate and can be considered as one of the major weakness of the Italy (MISE, 2015). The lack of R&D investments and the territorial development gap requires 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 [4].

INSERT TABLE 1

[4]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 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 2007-13 main objective is to enable the regions of the south 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. Italy allocate €9.6 billion to this priority, in particular through the "Research and Competitiveness" programme.

INSERT FIGURE 3

Figure 3 remarks the structural differences between Northern and Southern Regions, analysing the different objectives followed by the policies. The firsts are subjects to policies which aim 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.

3.2 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 using two different waves of the Community Innovation Survey[5] (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 centred on different countries. The definition of the dataset requires a preparatory identification of the firms participating to both CIS waves. This process allows to individuate more than 7000 firms. The introduction of indirect effects in our analysis 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 at unit level. 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 firms avoiding the presence of treated units in control group[6]. 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, reducing the sample size

[5]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).

[6]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.

to 2389 SMEs of which only 145 treated. This approach, focusing only on the creation of linkages between units in response to the treatment, allows to estimate both direct and indirect effects of the policies.

INSERT FIGURE 4

Figure 4 shows the geographical localization of the firms in relation of their own state of treatment. The majority of the units are concentrated in the north of the Italy, but the presence of isolated treated, located mainly on 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.

INSERT TABLE 2

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. Moreover, considering the objective of producing and testing a novel framework to include spatial interferences in causal analysis, an additional control is required to analyse the spatial distribution of the treatment variable, i.e. random or clustered. The presence of spatial autocorrelation is tested by the Moran's I Index evaluated on 4 different cut-off distances (40 km, 50 km, 75 km, 100 km). The 4 distinct cut-off allow to understand the spatial extension of the interferences and, in consequence, of the indirect effects.

INSERT TABLE 3

The results show a random spatial pattern of treatment variable at a cut-off distance equal to 40 km, whereas we find evidence of spatial clustering in all the other cases. This results allow to analyse how the presence of spatial autocorrelation in treatment variable influences the correctness of the estimates. In the next section we introduce the methodological approach proposed by Di Gennaro and Pellegrini (2016).

3.3 Econometric Model

The definition of a novel framework in which the interferences assume a fundamental role in the identification of the causal effects take inspiration from 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 depends on the sample size and the number of treated units. This consideration makes intractable the identification of the potential outcomes. However, restricting the extension of the interferences allows to overcome the identification problems. The approach followed in this paper, taking into account only the spatial dimension of the interactions between units, is based on a proximity function modelled on the state of treatment of the neighbours. Our method preserves the validity of the "traditional" potential outcome model (POM), even if the inclusion of the spatial interferences enables the decomposition of the overall causal impact in direct and indirect effects.

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

The POM in (2) corresponds to the equation in (1) plus/minus (1) itself pre-multiplied by D_j. The latter term represents neighbours' state of treatment and is obtained applying a spatial lag of the treatment variable. Moreover, (2) can be rearranged as:

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

Under the formulation in (3) we are able to identify both direct and indirect effects. More specifically, the first term in (3) represents the direct effect (i.e. the total effect purified by the impact of the interferences), while the latter individuates the indirect effect. This insight allows to decompose the ATE as the sum of direct and indirect effects, as briefly reported in (4).

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

This intuition constitutes the cornerstone of the Difference-in-Difference approach elaborated on the remainder of the paper. Therefore, the ongoing consideration leads us to a substantial review of the "traditional" Diff-in-Diff estimator. Recalling that β_3 represents the ATE estimated by the following equation:

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

which can be expressed in analogous way in term of expectactions:

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

(5) and (6) provides correct estimates of the ATE, although they omits the presence of interferences between units. In this paper, we introduce the interactions into the regression model in (5) adapting the line of reasoning in (2). In other words, we include an additional part in the "standard" DID multiplied by D_j to model the presence of spatial interactions.

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

The specification in (7) allows us to estimate simultaneously total, direct and indirect causal effects. Implementing the "standard" Diff-in-Diff approach to (7) provides unbiased estimates of the ATE. Notwithstanding, in this case we are able to decompose the ATE, identifying the effects attributable to the interferences. Thus, 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 terms $\overline{D_j^1}$ and $\overline{D_j^0}$ indicate, respectively, the average share of neighbours treated for subsidized and controls. As previously said, the ATE in (8) is obtained applying a double difference with respect to own state of treatment and time. The estimation of direct and indirect effects requires an introductory presentation of all the possible combinations by conditioning on time, own and neighbours' state of treatment

(i.e. $E[Y|D,t,D_j]$). Considering $D_j \neq 0$ allows to include the cases in which the treatment induces spatial interactions between units, i.e. in the neighbourhood of the considered unit is located at least one subsidised.

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

The direct effect (ADTE) is evaluated by a Diff-in-Diff on the units without neighbours' treated, i.e. ADTE comprehends the situation in which interactions as response to the treatment are absent. Along these lines, we obtain the ADTE as in (10):

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

Another feature of our model specification is the ability to provide differentiated indirect effect both on treated and controls. These effects are obtained through a double difference estimator on time and neighbours' treatment, keeping constant own state of treatment.

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

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

(11) and (12) constitute respectively the AITET (Average Indirect Treatment Effects on the Treated) and the AITENT (Average Indirect Treatment Effects on the Controls). The AITET (resp. AITENT) underlines the additional effect on the treated (resp. control) of being located in the neighbourhood of subsidized units. Next section is devoted to the implementation and the discussion of the results of the proposed methodology on Italian R&D policies.

4 Results

The objective of this paper is the evaluation of both direct and indirect additionality of Italian innovation policies. As mentioned above, the baseline data to elaborate our analysis consist of 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 as public policies in first instance stimulate innovation expenses, whereas the evaluation on R&D outputs and economic performance can require a longer time period that we cannot properly analyse 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)[7]. The choice of these variables is adherent for obtaining detailed information on the process of production of innovation

[7]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.

and R&D.
To ensure robust and unbiased estimates of both direct and indirect effects we follow the approach in Di Gennaro and Pellegrini (2016). The aforementioned authors demonstrate how the linear model is a correct estimator of the ATE, although it provides biased indirect effects. Under this approach, it becomes problematic to distinguish between the different components of the indirect effects, i.e. linear model is not able 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 ($D_j Dt$). The introduction of an alternative hierarchical specification, with heterogeneity at municipal level in the random effects, is therefore required to provide correct 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 of 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 correctness 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. In this way, the geographical extension of both direct and indirect effects is properly evaluated. Furthermore, we are able to identify the differentiated spatial trend between direct and indirect causal impacts obtaining information on their optimal dimension over space.

INSERT FIGURE 5

Figure 5, distinguishing by the different cut-off distances, reveals the share of neighbours treated for all the firms included in our analysis along Italian territory. Focusing on small distances, we underline 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, considering greater cut-off distances the spatial distribution exhibits, on average, 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[8]. This relation is deepened in the discussion of the results.

INSERT TABLES 4 AND 5

[8]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.

Firstly, we analyse total impact of the policies (model 1). The estimates demonstrate positive and significant ATE for almost all the outcome variables, with the exception of Total R&D per employee. This confirms the additionality of public policies on R&D expenses. Moreover, these results provides the benchmark of the decomposition process estimated by the alternative Difference in Difference models with spatial interferences [9].

Considering spatial interactions between units, we are able to observe significant and positive direct effects, particularly in relation to total and external R&D expenses (models 2 and 4). Direct effect is more intense of the total impact of the policies, 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 wider direct effect when distance increases, whereas we can observe an inverse relation between indirect effects and 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, but can have detrimental effects on the treated especially in presence of high level of spatial interferences.

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 distortion 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, although the upward bias, in absolute values, for both direct and indirect effects.

As indicated in the preceding section, the results of the Diff-in-Diff model with spatial interferences can be easily recombined in the ATE. Table 5 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 allowing a twofold consideration. On the one hand, looking at the complete models (i.e. 2 and 4) we can observe equal results of the AITET, but differentiated estimates for both ADTE and AITENT. As explained above, these results are influenced by the estimation procedure. Indeed, linear model does not correctly distinguish between different indirect effects, even if it is able to catch the overall impact of the same. Instead, hierarchical model is a good approximation of both total, direct and indirect effects, producing, on the whole, correct and more efficient estimates. This conclusion is in line with Di Gennaro and Pellegrini (2016).

On the other hand, the decomposition of the ATE shows a strong and positive direct additionality of the policies, but it provides contradictory results on the indirect effects. While the spillovers on the treated are negative and meaningful, indirect effects on the controls are of a negligible intensity. Furthermore, both direct and indirect effects are influenced by the distance. The relation between treatment effect and an increase in cut-off distance has a dual implication on the results. While direct effects increase with distance, we observe a decline of the indirect effects on treated and a substantial improvement of the spillovers on control. These results provide evidence on the role of geographical distance in causal analysis to fully analyse and understand the spatial dimension of both direct and indirect effects.

[9] 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.

5 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 to develop 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. Allowing for differentiated effects on treated and controls enable 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); meanwhile if the Public Authority seeks to optimize overall territorial competitiveness it is requested low-medium level of interactions[10]. Furthermore, this paper demonstrates the role of distance

[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 undeveloped areas. It seems reasonable

for estimating the spatial extension of both direct and indirect effects.

INSERT FIGURE 6

Figure 6 resumes the behaviour of treatment effects over space. Focusing on the trend of ADTE, we observe a stable path moving from short to medium distances, i.e. between 40 and 75 km. However, we note a substantial reinforcement of direct effect, with cut-off distance equal to 100 km. Conversely, AITET exhibit a similar, even if diverging, path in comparison with ADTE. More in detail, moving the cut-off distance from 40 to 75 km entail limited variations, while the 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 demonstrating 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.

to assume that this instrument aims to maximize the spillover effects.

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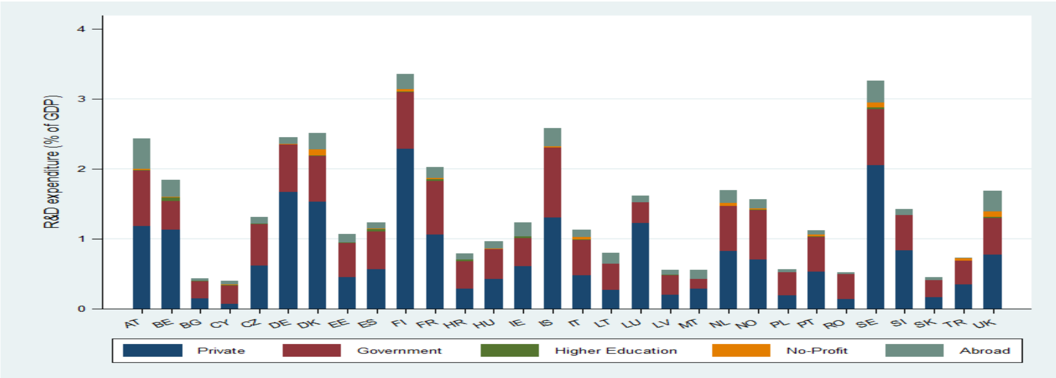
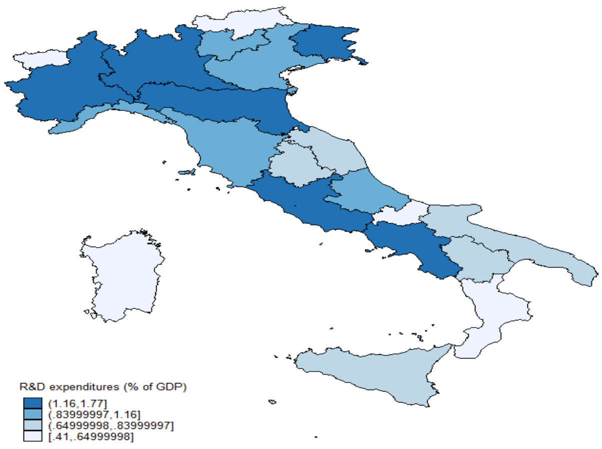
6 Figure and Tables

Figure 1: European R&D Expenditures by source of funds



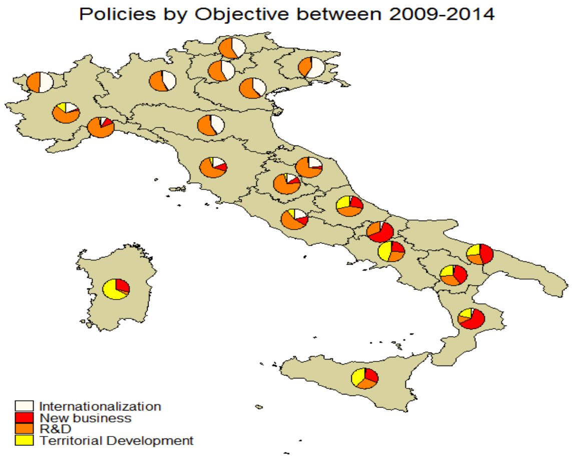
Source: Eurostat
Note: Figure 3 shows the R&D expenditures in EU by source of funds in GDP percentage for the year 2007.

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



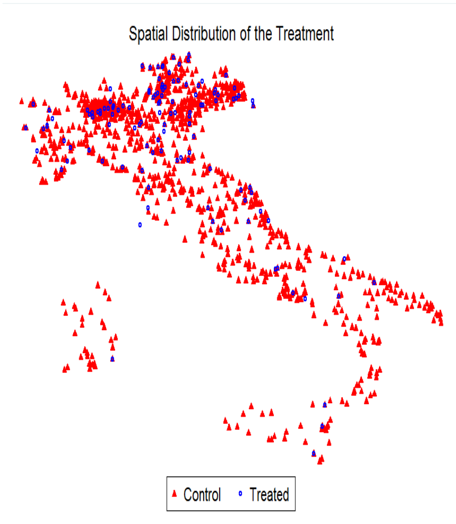
Source: Eurostat
Note: Figure 4 shows Italian Regional R&D expenditures for the year 2007. It demonstrates a greater propensity to R&D process for the Central and Northern Regions.

Figure 3: Objective of public policies



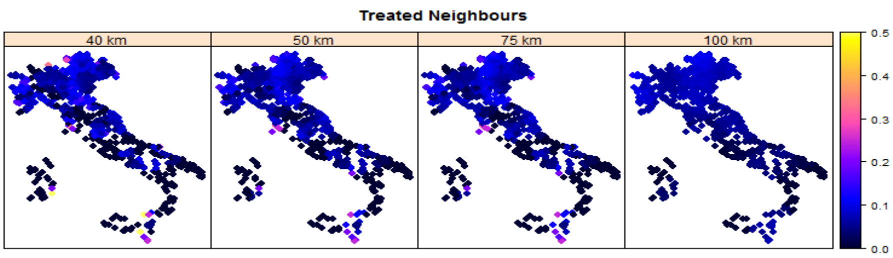
Note: Figure 5 shows the different objectives of the public policies distinguished by Region.

Figure 4: Spatial Distribution of the firms



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

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.

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 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)

Table 3: Moran I Index

Distance	Moran I Index	Expected Value	P-value
40 Km	0.0037	-0.0004	0.1840
50 Km	0.0076	-0.0004	0.0400
75 Km	0.0076	-0.0004	0.0080
100 Km	0.0089	-0.0004	0.0010

Source: Estimates of the Moran I index based on 1000 simulation

Table 4: Results

OUTCOME

		Total R&D				
		[1]	[2]	[3]	[4]	[5]
40	Dt	210227.4***	321544.8**	579792.4***	322829.3**	560744***
		[69328.8]	[131220.4]	[105588.4]	[128998.1]	[104315.1]
	Djt		-2453.3	-2453.3	19440.3	64078.3
			[265623.6]	[265900.2]	[295391.25]	[295376.5]
	DjDt		-1740489.6	-5778613***	-1762383.3	-5485135.5***
			[1746459.7]	[1250436.3]	[1718881.4]	[1241905.4]
50	Dt	210227.4***	317075.4**	836312.8***	319166.1**	806701.9***
		[69328.8]	[151726.5]	[118948.6]	[149330.7]	[117735.6]
	Djt		-109582.7	-109582.7	-74142.0	16734.4
			[320069.4]	[321043.7]	[364895.0]	[365632.1]
	DjDt		-1565786.5	-9234751***	-1601227.3	-8812187***
			[2002662.7]	[1438433.5]	[1974272.8]	[1430472.5]
75	Dt	210227.4***	257363.5	907051***	262226.4	869538.1***
		[69328.8]	[183465.1]	[139944.8]	[180659.0]	[138477.5]
	Djt		-50221.2	-50221.2	31781.5	172869.0
			[384978.9]	[386136.5]	[453418.7]	[453941.7]
	DjDt		-694491.4	-10344477***	-776494.1	-9812878***
			[2531868]	[1816324.1]	[2497161.5]	[1802749.3]
100	Dt	210227.4***	699105.9***	1622686.5***	699838.1***	1556882***
		[69328.8]	[229717.5]	[171128.2]	[226349.4]	[169816.5]
	Djt		136358.7	136358.7	149253.5	360663.2
			[438059.3]	[439662.5]	[529803.9]	[530607.7]
	DjDt		-7258381.5**	-20940528***	-7271276**	-19992560***
			[3254798]	[2330740.3]	[3211352]	[2317760.5]

		Internal R&D				
		[1]	[2]	[3]	[4]	[5]
40	Dt	85254.9**	-21882.5	215938.1***	-18851.7	202543.5***
		[38792.1]	[73382.2]	[59163.6]	[71665.9]	[58101.0]
	Djt		-7456.9	-7456.9	42937.0	86124.6
			[148544.2]	[148990.0]	[165973]	[166258.9]
	DjDt		1675694.8*	-2043020.6***	1625300.9Âř	-1839076.5***
			[976669.9]	[700648]	[955053.7]	[692208.7]
50	Dt	85254.9**	76498.2	476822.0***	80033.6	454193.5***
		[38792.1]	[84566.9]	[66487.2]	[82731.1]	[65458.1]
	Djt		-5646.5	-5646.5	53368.6	126729.8
			[178395.1]	[179449.8]	[204916.9]	[205892.3]
	DjDt		129968.4	-5782680.5***	70953.3	-5463511***
			[1116212.3]	[804023.3]	[1093964.5]	[795889.9]
75	Dt	85254.9**	76745.7	526025.6***	81925.8	500731.8***
		[38792.1]	[102389.3]	[78230.6]	[100198.5]	[76977.5]
	Djt		12864.5	12864.5	99699.4	204356.4
			[214851.4]	[215854.5]	[255562.3]	[256220.7]
	DjDt		124945.8	-6548331***	38110.9	-6194267***
			[1413000.4]	[1015344.9]	[1385237]	[1002568.2]
100	Dt	85254.9**	83825.8	808295.9***	86363.9	768595.6***
		[38792.1]	[128248.3]	[95886.5]	[125537.1]	[94613.3]
	Djt		53489.2	53489.2	96230.6	279364.9
			[244562.8]	[246351.5]	[299238.6]	[300592.4]
	DjDt		14887.8	-10717588***	-27853.6	-10156122***
			[1817111.5]	1305959.0	[1781330.9]	[1291727.1]

		External R&D				
		[1]	[2]	[3]	[4]	[5]
40	Dt	43571.4**	214291***	233369.0***	214361.9***	231258.3***
		[18674.5]	[35163.8]	[28265.1]	[34677.0]	[28017]
	Djt		-808.9	-808.9	417.5	3625.6
			[71180.5]	[71179.3]	[79494.9]	[79413.7]
	DjDt		-2669435.3***	-2967750***	-2670661.8***	-2935048.8***
			[468008]	[334731.4]	[462070.9]	[333574.3]
50	Dt	43571.4**	266426.9***	312577.3***	266711.8***	309128.9***
		[18674.5]	[40698]	[31816.7]	[40177.8]	[31595.9]
	Djt		-3767.2	-3767.2	1044.6	9098.7
			[85852.9]	[85873.7]	[98263.6]	[98213.7]
	DjDt		-3291078.3***	-3972703.5***	-3295890***	-3923281.3***
			[537178.9]	[384756.3]	[531189.8]	[383906.6]
75	Dt	43571.4**	234632.4***	304077.7***	235739.4***	299538***
		[18674.5]	[49384.6]	[37571.5]	[48774.3]	[37297.5]
	Djt		-6423.9	-6423.9	12166.8	27227.5
			[103627.5]	[103667.6]	[122594.3]	[122463]
	DjDt		-2837161.3***	-3868651.3***	-2855752***	-3805058.3***
			[681521]	[487635.6]	[674194]	[485573.7]
100	Dt	43571.4**	398763.8***	487814.4***	397758.0***	481707.7***
		[18674.5]	[61876.7]	[45944.3]	[61120.9]	[45726.0]
	Djt		814.3	814.3	-16002.9	5095.8
			[117995.5]	[118040.2]	[143367.4]	[143141.3]
	DjDt		-5262002.5***	-6581219.5***	-5245185.5***	-6491314.5***
			[876711.5]	[625754.9]	[867173.3]	[624117.1]

		Other R&D				
		[1]	[2]	[3]	[4]	[5]
40	Dt	81401.1**	129136.3*	130485.3**	129689*	125453.1**
		[36528.7]	[69370.1]	[55755.7]	[69024.5]	[55612.7]
	Djt		5812.5	5812.5	15205.3	14646.2
			[140422.7]	[140408.0]	[150123.7]	[150030.6]
	DjDt		-746749.1	-767842.7	-756141.9	-689876.3
			[923271.4]	[660290.1]	[919263.6]	[660257.1]
50	Dt	81401.1**	-25849.7	46913.6	-24773.2	39209.0
		[36528.7]	[80545.0]	[62960.2]	[80171.6]	[62825.1]
	Djt		-100169.0	-100169.0	-82020.1	-73729.2
			[169910.9]	169930.4	[184312.9]	[184210.8]
	DjDt		1595323.4	520633.6	1577174.5	631246.6
			[1063126.3]	[761371.8]	[1059152.4]	[761272.6]
75	Dt	81401.1**	-54014.7	76947.6	-52150.4	66348.2
		[36528.7]	[97270.3]	[73999.6]	[96853.3]	[73856.5]
	Djt		-56661.8	-56661.8	-25241.0	-8481.8
			[204109.8]	[204180.3]	[225247.2]	[225127.8]
	DjDt		2017724.0	72505.6	1986303.3	224331.6
			[1342356.8]	[960431.4]	[1337744.4]	[959891.9]
100	Dt	81401.1**	216516.3*	326576.2***	219294.1*	307179.6**
		[36528.7]	[122405.4]	[90861.1]	[121901.9]	[90837.4]
	Djt		82055.2	82055.2	128905.6	141575.6
			[233420.6]	[233440]	[261834.4]	[261697.2]
	DjDt		-2011266.8	-3641720.8***	-2058117.0	-3361561.8***
			1734324.8	[1237513.9]	[1728412]	[1238417.5]

		Total R&D per Employee				
		[1]	[2]	[3]	[4]	[5]
40	Dt	534.10	3776.5	5446.4**	3829.1	5240.2**
		[1698.1]	[3222.7]	[2590.5]	[3211.6]	[2586.5]
	Djt		21.0	21.0	911.1	1071.0
			[6523.6]	[6523.5]	[6905.1]	[6901.8]
	DjDt		-50701.7	-76814**	-51591.8	-73665.8**
			[42892.5]	30677.6	[42767.0]	[30692.2]
50	Dt	534.10	667.9	6269.7**	758.9	5887.6**
		[1698.1]	[3740.6]	[2925.1]	[3729.5]	[2921.7]
	Djt		-707.1	-707.1	824.5	1381.1
			[7890.9]	[7894.8]	[8440.9]	[8447.4]
	DjDt		-1896.8	-84634.2**	-3428.5	-79240**
			[49373.2]	[35372.8]	[49262.2]	[35385.9]
75	Dt	534.10	383.8	9099.8***	443.6	8575.9**
		[1698.1]	[4515.7]	[3437]	[4503.4]	[3433.8]
	Djt		1865.1	1865.1	2882.8	3810.5
			[9475.5]	[9483.3]	[10270.5]	[10280.9]
	DjDt		2023.2	-127438.2***	1005.5	-119890.5***
			[62317.2]	[44608.0]	[62189.9]	[44613.6]
100	Dt	534.10	4888.7	16749.7***	4980.6	15946.1**
		[1698.1]	[5680.1]	[4219.8]	[5665.5]	[4221.6]
	Djt		4159.4	4159.4	5718.6	6992.3
			[10831.6]	[10841.5]	[11880.0]	[11906.3]
	DjDt		-64998.7	-240710.4***	-66557.8	-229153.4***
			[80479.2]	[57472.9]	[80317.3]	[57541.9]

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

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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

Table 5: Decomposition of the ATE

			40				50				75				100			
			ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE
		[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
	Total R&D	[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
		[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
	Internal R&D	[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
		[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
OUTCOME	External R&D	[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
		[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
	Other R&D	[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
		[1]				534.1				534.1				534.1				534.1
	Total R&D	[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
	per Employee	[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

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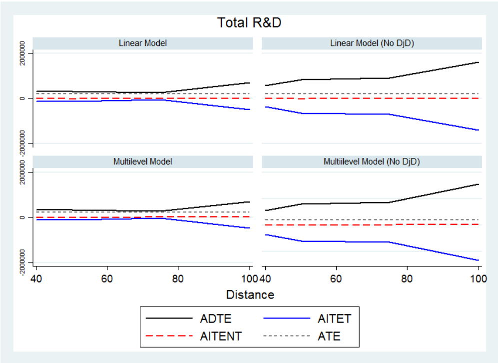
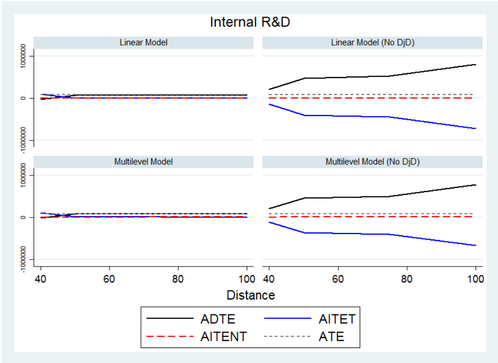
The inclusion or not of a treated unit in the neighbourhood of the others is calculated by different cut-off distances: 40 km, 50 km, 75 km, 100 km

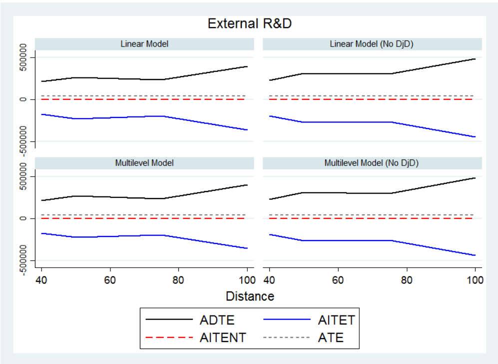
Figure 6: Treatment effects dynamics in function of the distances



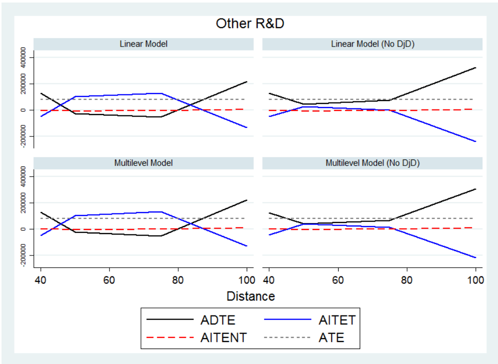
(a)



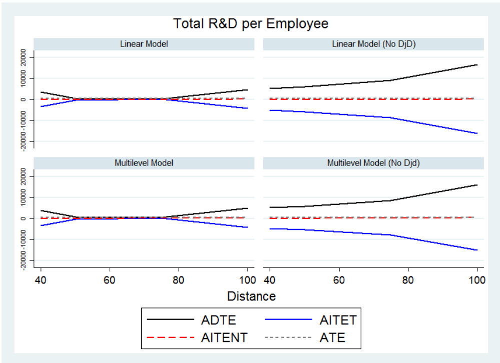
(b)



(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.