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Policy Evaluation and Spillover Effects

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Summary

During the last decades, major efforts are being made to address the identification problems in causal analysis in presence of interactions[1] between units. Within this framework, interferences have a twofold relevance. On the one hand, the recent reform of EU Cohesion Policies promotes the development of knowledge networks and scale effects in regions having both existing strengths and the potential for diversification in related sectors, activities, or technologies (McCann and Ortega-Argilés, 2013). Moreover, promoting the creation of linkages between institutions, firms and research centres, this approach aims to maximize knowledge spillovers and, on the whole, innovation and growth (Barca, 2009; Garcilazo and Oliveira Martins, 2015; Rodríguez-Pose and Wilkie, 2015).

On the other hand, Rubin Causal Model, being based on SUTVA hypothesis, explicitly rules out the occurrence of interactions between units (Rubin, 1974, 1977; Rosenbaum and Rubin, 1983), i.e. no-interference assumption states that the treatment of a unit does not depend on the state of treatment of the others. Assuming the validity of the SUTVA makes possible the evaluation of the causal effect of the treatment. Nonetheless, it cannot allow to estimate the occurrence of spillover effects. Starting from this point, this thesis aims to propose an alternative theoretical and methodological framework which, including interferences in causal analysis, enables the identification and estimation of both direct and indirect treatment effects.

In short, the major innovations introduced in this Thesis consist of the development of two alternative DID approaches. The first [2], considering the localization or not in agglomerated labour market areas, develops two different causal effects on the controls. The second approach[3] allows to decompose the ATE in both direct and indirect effects by means of a combination of spatial and hierarchical methodologies. This approach, including spatial interferences in the regression model of a Diff-in-Diff approach, demonstrates the unbiasdeness of the ATE even in presence of interactions. However, a correct estimation of total, direct and indirect effects requires the use of the novel SH-DID.

During the early stages of this research[4], I aimed to find an answer to the following questions:

- How we can include spillover effects in causal analysis?
- What is the dimension of proximity more adaptable to causal context?

[1]In the remainder of the thesis we use interchangeably the terms interactions and interferences.

[2]see Chapter 2.

[3]The evaluation of the performances of the SH-DID estimator is discussed in Chapter 3 by Montecarlo Simulation, while in Chapter 4 we propose an empirical application of the novel method.

[4]This dissertation is organized in 4 different, even if related, papers. To make an easier subdivision of the different contributes I devote a chapter for each papers in the thesis. Moreover, considering the shared reference literature, some repetitions are present in the text. However, every chapter of this dissertation proposes a different innovative contribute to existing literature.

- Is it possible to identify both direct and indirect effects?
- Is ATE, in presence of interferences, biased?

However, find a solution to this questions is not straightforward and has required an in-depth investigation of causal framework in presence of interferences. This analysis is included in Chapter 1. In Section 1.1 we introduce the concept of knowledge spillovers, remarking the key role played by different dimension of proximity in facilitating their diffusion (Boschma, 2005). Notwithstanding, our interest is limited to spatial and geographical proximity between units. This decision is compatible with policy evaluation framework, in particular when the aim of the researcher is the evaluation of the additionality of R&D policy on SMEs. Section 1.2 presents the actual state of the art of causal inference in presence of interactions between units. In literature we can distinguish the presence of three distinct approaches.
The first, which we can define the "empirical" approach, suggests the development of appropriate causal estimands to determine the additional effects of the interferences[5] (Cerqua and Pellegrini, 2014; Verbitsky-Savitz and Raudenbush, 2012; Sobel, 2006). The second approach identifies spillover effects designing multi-level experiment (Sinclair et al., 2012). Finally, Manski (1993) assumes the impossibility to distinguish between endogenous and contextual interactions, i.e. the so-called "Reflection Problem". Solutions to the identification problems includes alternative approaches to the linear-in-mean model (Brock and Durlauf, 2001; Moffitt, 2001), restrictions on the shape of response function (Manski, 2013) and estimation of structural interaction effects (Lee, 2006). The methodological implication of the "Reflection Problem" is explained in Section 1.3.
Moreover, we show how, in presence of interferences between units, linear model allows to identify only the overall effect of neighbours' characteristic. Notwithstanding, spatial and hierarchical methodologies allows to address the identification problems of causal effects [6] (Gibbons and Overman, 2012; Corrado and Fingleton, 2012; Gibbons et al., 2014). In Section 1.4 we discuss how the novel approaches presented in the remainder of the thesis can be placed in the context of the actual literature on policy evaluation.
The methodological innovation proposed in Chapter 2 is a novel spatial Difference-in-Differences estimator. This estimator is used to evaluate the effectiveness of R&D incentives to private firms allocated by Region Umbria in the period between 2004 and 2009[7]. Our approach compares distinct treatment effects on the basis of the localization in the main local market areas of Umbria (Perugia and Terni). In this way we are able to control for the presence of technological spillovers due to both geographical and economic proximity (see Section 2.2).

[5] The "empirical" approach is the one followed in Chapter 2.

[6] A combination of spatial and hierarchical techniques is implement in Chapters 3 and 4 by the development of a novel SH-DID model.

[7] The analysis of the characteristics of the policies and the dataset is presented in Section 2.1.

The peculiarity of our approach is to consider the presence of interactions within the LMAs, assuming a limitation on the validity of the SUTVA limited to firms located in different LMAs. Therefore, our assumption imposes the restriction that the interferences among subsidized and controls are relevant only inside the LMAs and not significant outside. Under this assumption, we develop a framework which makes possible the estimation of two specific causal effects:

Average Treatment Effect using the Influenced Controls (ATEIC):

$$\begin{aligned} ATEIC =& E[y_i|D_i = 1, t_i = 1, LMA = 1] - E[y_i|D_i = 1, t_i = 0, LMA = 1] - \\ & E[y_i|D_i = 0, t_i = 1, LMA = 1] - E[y_i|D_i = 0, t_i = 0, LMA = 1] \end{aligned}$$

Average Treatment Effect using the Uninfluenced Control (ATEUC):

$$\begin{aligned} ATEUC =& E[y_i|D_i = 1, t_i = 1, LMA = 1] - E[y_i|D_i = 1, t_i = 0, LMA = 1] - \\ & E[y_i|D_i = 0, t_i = 1, LMA = 0] - E[y_i|D_i = 0, t_i = 0, LMA = 0] \end{aligned}$$

The ATEIC and the ATEUC allow diversified impacts, depending on the choice of the controls. The ATEUC represents the impact of the subsidies, taking into account the interferences; the ATEIC is a measure of the error in the estimation of the effects when we wrongly assume the validity of the SUTVA. However, the difference between ATEUC and ATEIC provides a measure of the spillover effects in response of the subsidies.
The results, presented in 2.3, show a positive and significant impact of the incentives, in particular for innovative outputs and the small firms. The magnitude of the impact is influenced by geographical localization. The effect is higher on controls located outside the main labour market areas, suggesting the presence of significant local technological spillovers. To conclude, we have demonstrated how geographical localization and market concentration can play a determinant role in estimating the effectiveness of the policies.
An alternative solution to identification problems in presence of interferences is presented in Chapter 3. In this section we propose a causal framework[8] within a new spatial hierarchical Difference-in-Differences model (SH-DID). The "traditional" DID model provides unbiased estimates of the treatment effect, even if it omits the occurrence of interactions between units. Including interferences in causal analysis requires, therefore, a substantial review of the Diff-in-Diffs approach (see Section 3.2).
In this chapter, the interactions are approximated through a function based on neighbours' state of treatment (D_j). In this way, we include in the regression model of a Diff-in-Diff the variable D_j and its interaction with own state of treatment and the temporal dummy:

$$Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j D + \beta_6 D_j Dt \tag{0.1}$$

[8] See Section 3.1.

Applying the "standard" Diff-in-Diffs approach to 0.1 we obtain the following ATE

$$ATE = \beta_3 + \beta_4(\overline{D_j^1} - \overline{D_j^0}) + \beta_6\overline{D_j^1} \tag{0.2}$$

The term $\overline{D_j^1}$ (resp. $\overline{D_j^0}$) indicates the average share of treated neighbours for subsidized (resp. control) units. Under the formulation in 0.1 is possible to compute both direct and indirect impact of the policies. The direct effect (ADTE) is estimated by the Diff-in-Diffs for the units without treated in their neighbourhood, i.e. the ADTE represents the situation in which there are not interactions due to the treatment.
Furthermore, model specification allows to estimated differentiated indirect effects on treated and controls. The indirect effects are obtained through a double difference estimator with respect to time and D_j, assuming own state of treatment constant. To resume, the novel approach allows to define three distinct treatment effects[9]:

- $ADTE = \beta_3$
- $AITET = \beta_4\overline{D_j^1} + \beta_6\overline{D_j^1}$
- $AITENT = \beta_4\overline{D_j^0}$

The performances of the SH-DID are evaluated by a Montecarlo Simulation in Section 3.3. The results confirm how omitting the presence of interferences produces biased parameters of direct and indirect effects, even if the estimates of the ATE in the linear model are unbiased. Conversely, the SH-DID provides unbiased estimates of total, direct and indirect effects. In addition, this model is the more efficient compared both to the traditional and a Spatial modified Difference-in-Differences estimator.
Chapter 4 presents an empirical application of the SH-DID approach. This Chapter examines the additionality of R&D policies distributed to Italian firms. In detail, we evaluate policy effectiveness on R&D expenses using two different waves of the Community Innovation Surveys[10]. The estimates in Section 4.4 demonstrate 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, distance influences the results, i.e. increasing the cut-off distance increase, in absolute value, the intensity of the effects. To conclude, this thesis proposes a suitable empirical framework able to take into account the inclusion of interferences between units in causal analysis. Furthermore, our novel approaches could constitute a turning point on the definition of political priority and efficiency of EU policies to promote knowledge spillovers and local competitiveness.

[9] A complete description of direct and indirect effects is provided in Sections 3.2,3.A and 3.B.

[10] Section 4.3 shows a summary of the policies implemented in Italy in the period between 2007-2013. Furthermore, this section discusses the construction of the dataset.

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Chapter 1

Causal analysis and spillover effects

Many empirical questions in economics and other social sciences depend on causal effects of programs or policies. Over the lasts decades, econometric and statistical analysis devote major efforts for improving the correctness of the evaluation of the effects of the policies. Nowadays, causal analysis reaches a level of development that makes it a fundamental approach in many areas of empirical research in economics, including labour, development and behavioural economics or studies focused on education. Despite the relevance of causal analysis in such branches, this thesis focuses only on the study of causal analysis in policy evaluation. In detail, in the remainder of this research we propose an in-depth analysis on the relationship between R&D policies and the formation of spillover effects.
Combine these two concepts is not straightforward, but a substantial reconsideration of traditional causal approach is needed. In point of fact, a large part of the recent literature on program evaluation focuses on estimation of the Average Treatment Effect (ATE) under the methodological framework proposed in the seminal works of Rubin (1974, 1977) and Rosenbaum and Rubin (1983). Rubin's formulation of causal inference problem, labelled Rubin Causal Model (RCM) by Holland (1986), is recognized as the fundamental guideline in both econometric and statistic literature. RCM, relying on potential outcome framework, allows the identification of the causal impact under the assumption of "no interference between difference units". This hypothesis, proposed by Cox (1959) and formalized in Rubin (1980, 1986), constitutes a part of the SUTVA [1].
Assuming the validity of the SUTVA in traditional experimental approach implies the consideration of interferences between units as nuisance terms. In this context, researchers aim to model studies able to produce unbiased treatment effects by eliminating the presence of interferences. Although, the validity of the SUTVA explicitly rules out spillover effects

[1] 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] from the evaluation of policy effectiveness. In this sense, the incompatibility between SUTVA and identification of indirect effects is clear. Nonetheless, during the last decade major efforts are devoted to the development of experimental methods to include interactions in causal analysis. The promotion of a novel framework from the perspectives of both regional economists and policy-makers has a twofold relevance.
In recent years, research on urban and regional economics directs more attention on empirical studies. Baum-Snow and Ferreira (2014), analysing the evolution of research in these branches, remark a growing trend of the number of empirical publication on the Journal of Urban Economics. In detail, while in 1990 only the 49% of the works were empirical, after 20 years they become the 71% of overall publications. The increased interest of scientists to empirical approach is a consequence of the refinement of the methodologies or it can be considered the reflection of the reform process of regional policies? The development of place-based policies can be correctly evaluate under the traditional framework or it requires a novel approach able to take into account the formation of an additional ”indirect” causal impact?
On one hand, Baum-Snow and Ferreira (2014), analysing the development of methodologies, show how, in 1990, only a handful of papers attempt to deal with omitted variables problems, while more than half of the total number of empirical publications, in 2010, use at least one research design that is more sophisticated than simple OLS, such as differences in differences, instrumental variables or matching. Furthermore, the role played by research and development as a tool to foster innovation and growth assumes a primary relevance in recent regional policies. In particular, considering EU, the cornerstone in current cohesion policy is the concept of ”Smart Specialization”[3] based on the principles of a ”smart, sustainable and inclusive growth”.
Smart Specialization, taking into account the economical heterogeneity between European regions (von Tunzelmann, 2009), attempts to find a solution on the productivity gap between Europe and USA. This novel approach focuses on vertical and non-neutral logic of intervention. In other terms, it promotes a process of identification and selection of desirable areas for intervention that could be favoured within the framework of the regional policy (Foray and Goenaga, 2013). The identification of correct areas of specialization is obtained by an entrepreneurial discovery process (EDP).
In the simplest sense, EDP is an exercise that ”reveals what a country does best in terms of R&D and innovation” and is widely recognized as a fundamental feature to put conceptual distances between the previous (horizontal) and actual (bottom-up) policy framework (Coffano and Foray, 2014; Capello, 2014). Anyway, this concept requires a complex and

[2] In this dissertation I will use the exchangeable term ”indirect effects” to refer to spillovers. In similar way, the interaction between units is also called interferences.

[3] See Europe 2020 Flagship Initiative Innovation Union [COM(2010)546]; The EU Budget Review [COM(2010)700]

interactive collaboration between private and public agents. This interaction is based on the coordinating capacity of private agents (i.e. firms) and the proactive role of public agents (i.e. the state) to make easier and stimulate the entrepreneurial discovery process (Foray et al., 2011). The heavy emphasis on the role of EDP might be construed as a neo-liberal plea for a laissez-faire strategy, even if smart specialisation confers a broadest sense to entrepreneurial knowledge, including a wide array of agents and institutions like firms, universities, public laboratories, etc. (Morgan, 2015).

In addition, this process allows the sharing of information between local governments and stakeholders with beneficial effect on local development and, potentially, on the entire economic system (Barca, 2009; Garcilazo and Oliveira Martins, 2015). Rodríguez-Pose and Wilkie (2015), remarking the fundamental role played by interactions between public and private agents in EDP, suggest the development of process able to facilitate communication between policy-maker and entrepreneurial agents. This process makes easier the aggregation and synthesis of entrepreneurial knowledge and, as consequence, the implementation of correctly designed place-based policies.

Notwithstanding, institutional environment constitutes a critical factor in creating this cooperative behaviour. It requires strong and well-functioning institutions to facilitate dialogue, interaction and overall closeness to enable the effective communication of entrepreneurial knowledge. Furthermore, the reinforcement in connectivity between developed areas and peripheral regions is optimized by the identification and strengthening of local areas of specialization. In this way, it is possible to maximize knowledge spillovers and innovation in both areas[4] OECD (2009a,b).

Foray and Goenaga (2013), on this issue: *"The reward for entrepreneurial discoveries has to be structured in such a way that it will maximize these spillovers... When the initial experiment and discovery are successful and diffused, other agents are induced to shift investments away from older domains with less potential for growth than the new one. Entry is a key ingredient of smart specialisation so that agglomeration externalities can be realised."*

The above mentioned authors highlight the different potential impact on both followers and leader regions. On one hand, the firsts, by implementing smart specialization strategy, become able to capture knowledge spillovers from the leaders. Following regions improve their capacity to attract future knowledge assets by becoming part of a competitive environment and creating a market niche. Conversely, leader regions is characterized by systems in which discoveries are made continuously. This process enables the development of new activities and strategic diversification, stimulating a dynamic innovation process. Nonetheless, this proactive environment requires adaptive policies able to identify and support new waves of technological opportunities.

Agrawal et al. (2010) recognise a key success factor in power market. These authors high-

[4] For further information on the topic : Krugman and Venables (1995); Fujita et al. (2001)

light a scarce propensity to share information and know-how from outside when innovation is concentrated in a single large firm. In other words, the maximization of knowledge spillovers requires a competitive innovation process characterized by many active and cooperative agents. To summarize, this approach considers the reinforcement on connectivity between different areas and ”place-based” policies as a key-factor in developing and diffusing knowledge spillovers. In this context, makes visible the paths and the extension of the spillover effects becomes crucial from policy-maker perspective, even if it still constitutes one of the main ”challenges” to be addressed by causal analysis and policy evaluation.
Indeed, including indirect effects in ”standard” causal framework implies a substantial review of the SUTVA and a reconsideration of the role covered by interactions between units. This dissertation aims to recombine in a unique theoretical framework the concepts of spillovers and policy evaluation. The development of a conceptual link between these separate, even if closely related, fields requires the identification of a methodological framework able to play the role of ideal "bridge". As we will explain later, combining spatial econometrics and hierarchical approaches enables to take into account, simultaneously, the evaluation of treatment and spillover effects, overcoming the identification problems in presence of interferences. More in detail, while spatial econometrics allows to model the function for designing interferences, hierarchical approach enables the check for local heterogeneity, improving the correctness and efficiency of the estimates.
The remainder of the introductory chapter reviews the literature on spillover and causal analysis. In section 1.1 we focus on knowledge spillovers and their process of spatial diffusion; section 1.2 explains the traditional assumption of ”causal analysis”, analysing how literature debates the inclusion of interferences between units. Section 1.3 focuses on the problem of identification in presence of interaction and recombine all the different concepts presented in the previous parts to lay the foundations for the development of a unique conceptual framework.

1.1 Spillovers

Technological spillovers facilitate the transmission of knowledge and ideas between firms, researchers and research teams. Literature, usually, classifies knowledge and the related spillovers in two distinct categories: codified or tacit. The first can be formally articulated and easily transmitted to others agents without direct social interactions (e.g. by books, documents, procedures); conversely, tacit knowledge is difficult to articulate and it requires the occurrence of interactive social networks (face-to-face relations) to be shared.
Fershtman and Gandal (2011) propose an intuitive example to distinguish between the two different typologies of knowledge spillovers. Considering the case of academic research they observe as researchers can acquire knowledge without interactions with other authors (i.e.

by reading and studying their works) or deciding to cooperate with co-authors or colleagues. Another good example can be found in R&D production process implemented by a firm. In this case, innovation can be developed with internal skills accumulated by the exposition or study of outer innovation or technologies or trough an interactive and cooperative process between individuals based on the discussion and exchange of information and new ideas.
Boschma (2005) proposes a classification of the role covered by different typologies of proximity (cognitive, organizational, social, institutional and geographical) in diffusing innovation. However, in this chapter we focus on the review of the literature only on social and geographical proximity. In this way, we restrict our analysis to tacit knowledge spillovers, considering the relevance of spatial and social dimension of tacit spillovers. More specifically, the notion of social proximity originates from the embeddedness literature (Polanyi, 1966), remarking the embeddedness of economic relations in a social context.
Uzzi (1997) suggests a mixture of both embedded and market relationship at network level to secure social proximity. However, too high level of social behaviour can be detrimental, turning the positive effect of the interactions in negative. From policy perspective, this is mainly due to the continuous evolution of the policies in conditions of uncertainty. On the other hand, trust between economic actors is negatively influences by weak level of social proximity. In this way, the lack of confidence between agents affects entrepreneurial discovery process and, in broader terms, smart policies (Foray and Goenaga, 2013). It is therefore clear that an optimal level of social proximity is required to maximize the positive effects of interactions.
Otherwise, geographical proximity refers to spatial or physical distance between economic entities. Spatially concentrated agents take benefit from positive spatial externalities, i.e. little distances favour informal contacts and an easier exchange of tacit knowledge. Howells (2002), considering the pervasiveness of codified knowledge, rethinks this concept for the case in which its assimilation can still require tacit knowledge and spatial closeness.
The seminal paper of Marshall (1920) provides the first intuition on the positive relation between spatial proximity, firms interactions and knowledge diffusion, i.e. closely located agents have easier interactions. More recently, Economic Geography and Endogenous Growth models provide further evidences on the relevance of spatial proximity in knowledge diffusion. Explaining the differences in regional growth, these approaches argue that geographically constrained knowledge externalities can give rise to increasing returns and localized economic growth (Lucas, 1988; Martin and Ottaviano, 1999; Baldwin and Forslid, 2005).
A strong empirical evidence in support of the spatial dimension of knowledge externalities is illustrated by the so-called "Geography of Innovation"Audretsch and Feldman (2004)[5]. The

[5]The literature on the Geography of Innovation is based on the pioneering works of Jaffe (1989), Acs and Audretsch (1991), Jaffe et al. (1993), Feldman (1994), Audretsch and Feldman (1996, 2004), Anselin et al. (1997) and Almeida and Kogut (1997).

aforementioned authors argue that: *"Incorporating spatial relationships into the model of the knowledge production function has redeemed the view that knowledge inputs are linked to innovative output. While the boundaries of the firm still matter, so do the boundaries of spatial agglomerations ..... The model of the knowledge production has been found to hold better for spatial units of observation than for enterprises in isolation of spatial context".*
This strand of the literature aims to deepen the relationship between the mechanism that cause the formation of knowledge spillovers and the degree to which these processes are geographically localized. The full understanding of this point has relevant policy implication. Indeed, a theoretical justification to R&D policies is based on the role played by knowledge spillovers on endogenous growth (Romer, 1986; Lucas, 1988, 1993; Grossman and Helpman, 1993).
Audretsch and Feldman (2004) and Van Oort (2002) provide evidence in support of the existence of geographical boundaries for knowledge externalities[6]. The so-called economy of agglomeration individuates a further important factor in explaining how proximity influences innovation. Agglomeration forces tend to concentrate universities, research centres and their facilities making possible an easier, faster and cheaper flow of information between agents Doloreux (2002).
de Groot et al. (2008), evaluating the statistical robustness of the evidence that agglomeration externalities lead to innovation and regional development, find strong indications in support of sectoral, temporal and spatial heterogeneity for the effects of specialization, diversity, and competition on regional and urban development. Nonetheless, the relevance of proximity in developing knowledge spillovers is acknowledged in literature, there is not still an explanation on the reason why they occur. Krugman (1991) advises that empirical measurement of knowledge spillovers could be impossible because *" knowledge flows are invisible, they leave no paper trail by which they may be measured and tracked".*
To make "visible the invisible" different data is used to approximate knowledge flows, including indicators related to relationship networks between researchers, e.g. knowledge-sharing relations (Giuliani and Bell, 2005), joint participation in R&D projects (Balland, 2012), joint patents (Ter Wal, 2013) and patents citations (Agrawal et al., 2006; Breschi and Lissoni, 2009; Buzard et al., 2015). Roach and Cohen (2013) propose to analyse the citations reported in the document of the patents to track public-knowledge flows.
The inclusion of network theory in studying proximity allows to take into account all the possible type of relationships between actors whereby innovation can be transmitted. This approach considers geographical proximity neither a sufficient nor a necessary condition for learning and innovation processes (Boschma, 2005). Giuliani (2007), bearing in mind the uneven and selective formation of clusters, underlines the partially irrelevance of geographical co-location in transmitting innovation.

[6]Breschi and Lissoni (2001) present a critical review on the so called "Localized Knowledge Spillover" literature.

Marrocu et al. (2011) confirm the complementarity among the different typologies of proximity. The aforementioned authors, developing a spatial Knowledge Production Function (KPF) at European regional level, demonstrate the relevance of both technological and geographical proximities, even if their results can be improved by a finest territorial and sectoral disaggregation.
Balland et al. (2015) suggest to take into account all short and long distances relationships to enable a proper clarification of the specific role played by geographical proximity, i.e. they recommend to limit the analysis on a particular location to better understand the interactions within and between clusters, rather than adopting a wide scale approach.
Despite evidence in support to micro-founded analysis in the estimation of knowledge spillovers, empirical literature is still scarce and fragmented. Indeed, mainstream literature, to the best of our knowledge, proposes a series of studies limited at national (Borowiecki, 2012; Kramar, 2009) or European levels (De Dominicis et al., 2013; Guastella and Van Oort, 2011; Ponds et al., 2010; Paci et al., 2014).
In addition, Charlot et al. (2012), remarking as different industries or technology sector can show different innovative patterns not fully captured by aggregated analysis, underline that the use of KPF is not problem-free. Moreover, patent intensity can underestimate the results for peripheral areas ruling out the occurrence of different forms of innovation, e.g. incremental or process innovation.
The recent developments of spatial econometrics tools allow to deal, in a direct way, the spatial dimension of the data and the occurrence of autocorrelation and heterogeneity in localized dataset (Anselin, 1988). LeSage and Pace (2009), analysing the relation between space and innovation (Marshall, 1920), provide an "R&D-based motivation" based on the idea that knowledge can be considered, at least partly, a public good, i.e. new agents can make use of it without any costs or at a lower cost that the one requested to produce it.
The assumption of spatially bounded knowledge externalities is at the heart of both geography and growth novel theories. This assumption allows to explain both agglomeration processes and uneven spatial distribution of economic activities. Furthermore, including directly spatial dependence in the model enable to take into account the strong spatial polarization of economic activities (Feldman, 1994; Vertova, 2002).
However, the debate on knowledge spillover is not limited to academic analysis, but it has become a central pillar in policy-maker conducts. Recently, EU policy-makers produces a series of intervention, included in the multi-annual project Horizon 2020, aimed at developing network externalities and strengthening more developed areas. Notwithstanding, the ambitious objectives of the policy makers cannot be properly evaluated by the mainstream approach in causal analysis. In this sense, a substantial reconsideration of the role played by interferences between units in causal framework is needed.

1.2 Mainstream approach in policy evaluation

Mainstream approach in policy evaluation, ruling out the presence of spillovers, focuses on the assessment of public policies effectiveness. From policy perspective, the concept of spillover assumes a twofold relevance. On one hand, the spatial extent of knowledge spillovers constitutes an important factor in shaping regional conditions for innovation and research. On this topic, part of the literature focuses on the pertinence of geographical space in diffusing knowledge spillovers through the introduction of concepts such industrial districts (Porter, 1998), innovation network (Camagni, 1991) and regional innovation systems (Fritsch and Slavtchev, 2011). This idea enables to analyse the supporting role of vehicle played by cooperative relationship between regional actors in the formation of spillovers. Policies can stimulate a wider and faster diffusion of knowledge spillovers by the formation of cooperative behaviour between units, i.e. incentives devoted to the formation of stable network of firms.
On the other hand, policy-makers implement public policies to promote competitiveness and growth by the creation of connections between agents. In this way, they implicitly disclose an additional channel which contributes to the process of development and dissemination of knowledge spillovers. The estimation of this supplementary channel constitutes a great challenge in causal analysis, requiring the identification of indirect effect in response to the policies.
Notwithstanding, under the traditional causal framework it is not yet possible estimate the additional "indirect" effect. In other words, causal analysis should not be limited to the evaluation of policy effectiveness by itself and a wider interpretation of the causal framework is needed to take into account total, direct and indirect effects. Nevertheless the improvement in methodological techniques[7], the problems of the identification and estimation of causal

[7] The literature focused in the analysis of randomized experiments started with the seminal works of Fisher (1925) and Neyman (1923), but the formulation of the dominant approach to the analysis of causal effects in observational studies was developed only 50 years later (Rubin, 1973a,b, 1974, 1977, 1978). Rubin proposed the interpretation of causal statement as comparisons of so-called potential outcomes: pairs of outcomes defined for the same unit given different levels of exposure to the treatment. RubinâĂŹs formulation of the problem of causal inference, labeled the Rubin Causal Model (RCM) by Holland (1986), quickly becomes the standard in both statistics and econometrics literature. After the precursory works of Rubin the causal analysis framework has known a period of continuous growth, both from methodological than empirical viewpoint, improving the possibility of implementing correct and unbiased estimates of the treatment effects. The problem of identification and estimation of the policy effects is greatly simplified by means of the unconfoundedness or selection on observables, assumptions that remove all biases between treated and control units, adjusting for differences in observed covariates, or pretreatment variables (Rubin, 1977). This case is of great practical relevance, with many studies relying on some form of this assumption. Semi-parametric efficiency bound has been calculated for this case (Hahn, 1998; Frölich, 2004; Busso et al., 2014; Tan, 2006; Huber et al., 2013) and various semi-parametric estimators have been proposed (Heckman et al., 1997; Hirano et al., 2003; Chen et al., 2008; Imbens et al., 2005; Abadie and Imbens, 2006, 2009; MaCurdy et al., 2011; Lee, 2013). Without unconfoundedness there is no general approach to estimate treatment effects. Various methods have been proposed for special cases, including sensitivity analysis (Rosenbaum and Rubin, 1983; Rosenbaum, 1995), bounds analysis (Manski, 1990, 2007; Imbens and Manski, 2004), instrumental variables (Angrist and Imbens, 1995; Angrist et al., 1996;

effects is not yet completely solved and requires a deepen analysis.
In RCM approach, the estimation of the causal effects relies on the validity of the Stable Unit Treatment Value Assumption (SUTVA; Rubin (1980, 1990)), also known as Individualistic Treatment Response (ITR) to remark the restriction that it imposes to the form of treatment response functions (Manski, 2013). SUTVA combines two different assumptions: ”no hidden versions” of the treatment and the absence of interferences between units, i.e. the treatment assignment of one unit does not affect the potential outcomes of the others. Defining Y and D respectively as the potential outcome and the treatment variable and indicating the i-th units of a population as $i = 1, \ldots, n$ we can resume the SUTVA as follows:

- **No hidden versions:** $Y_i(d) = Y_i$ when $D_i = d$. In presence of a single version of the treatment the way in which D_i is set equal to d is irrelevant and $Y_i(d) = Y_i$ is well defined.
- **No interference:** $Y_i(D_i, D_{-i}) = Y_i(D_i)$. This implies that the potential outcome of one unit can be considered as a function of only its own state of treatment.

In recent decades, SUTVA assumption has represented the "gold standard" in the identification and evaluation of causal effects, even though assuming the presence of a single version of the treatment or reclaiming the no-interference assumption is not always preferable.
Let us consider, for example, a medical trial in which different levels of medicine are administered to patients or two firms located in the same area that share the same market but only one of them is subsidized. This two cases are clear examples in which, respectively, the no-hidden version and the no interference assumptions are violated. Despite the relevance of the case in which the no-hidden version of the treatment is violated[8], the analysis proposed in this dissertation focuses only on the violation of the no interference assumption.
Recently, great attention has been paid in causal analysis to the study of the case in which the no interferences hypothesis is violated. As previously discussed, this is mainly due to a renovated interest discernible in policy-maker behaviours and a substantial improvement in methodological techniques. On the last point, the introduction and empowerment of social network, hierarchical and spatial econometrics theories enables to consider the presence of social, spatial and economic relation between units. Transposing this intuition on industrial policies, the novel methodologies allows to take into account the occurrence of interactions

DiPrete and Gangl, 2004), regression discontinuity design (Van der Klaauw, 2002; Hahn et al., 2001; Lee, 2001; Imbens and Lemieux, 2008; Imbens and Kalyanaraman, 2011; Lee and Lemieux, 2009; McCrary, 2008) or differenceâĂŞinâĂŞdifferences (Ashenfelter and Card, 1985; Abadie, 2005; Bertrand et al., 2002; Donald and Lang, 2007; Athey and Imbens, 2006; Puhani, 2012; Reggio and Mora, 2012). Further development has been introduced in order to consider quantile treatment effects (Firpo, 2007; Frölich and Melly, 2013; Chernozhukov and Hansen, 2005; Fortin et al., 2011; Frandsen et al., 2012), marginal treatment effects (Carneiro et al., 2010; Moffitt, 2008), bayesian causal effects (Rubin, 1978; Chen et al., 2009; Heckman et al., 2014; Talbot et al., 2015) and standard error robust technique (Solon et al., 2015; Cameron et al., 2008).

[8]The violation of the no-hidden version of the treatment is considered in detail by: VanderWeele and Hernan (2013) and Schwartz et al. (2012).

between firms stimulating academic debate on the development of a framework able to capture the formation of spillovers.

For the above reasons, major efforts are devoted to analyse the causal framework under interference. This interest can be found in different disciplines[9], including economics. The first step of an introductory analysis of the literature on causal inference in presence of interferences passes trough the definition of the causal effect of interest. On this regard, Hudgens and Halloran (2012) define the concepts of direct and indirect effect. The first corresponds to the response of the individuals to the treatment, whereas we can consider the indirect impact as the response to the interferences between units.

Considering the definition of indirect effects, why their knowledge is important? How we can define the interferences? The reply to the first question is not straightforward. Indeed, the knowledge of indirect effects has a twofold impact on causal analysis. On one hand, it can ensure unbiased estimates of treatment effects, allowing to decompose the total impact of the policies in its direct and indirect component. Furthermore, indirect effects played 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. In literature, research on drawing inference on causal effects in presence of interference is not yet common, although some exceptions exist (Verbitsky and Raudenbush, 2004; Sobel, 2006; Rosenbaum, 2012; Tchetgen and VanderWeele, 2010; Hudgens and Halloran, 2012; Kao and Toulis, 2013; De Castris and Pellegrini, 2015).

In spite of this, the majority of the literature is theoretical and/or oriented to randomized experiments, while applications dealing with violation of the SUTVA in the context of observational studies are, hitherto, uncommon. Cerqua and Pellegrini (2014) and Di Gennaro and Pellegrini (2016a)[10] propose two different approaches to isolate the presence of spillover. The first, considering untreated firms until a certain cut-off distance as affected, evaluates the presence of spillovers through a CEM-matching between affected and other controls. The latter produces differentiate estimates both for treated and untreated on the basis of the market concentration in which they operate. In this way, is possible to identify the presence of spillover effects through a comparison between the more concentrated subsidized and the two controls sub-samples.

[9] Application of causal inference in presence of interferences can be retrieved in education (Heckman et al., 1998; Hong and Raudenbush, 2012), infectious disease (Hudgens and Halloran, 2012; Tchetgen and VanderWeele, 2010) and econometrics (Graham, 2008; Manski, 2013; Sinclair et al., 2012).

[10] This paper constitutes the second chapter of this dissertation

Verbitsky-Savitz and Raudenbush (2012), analysing the causal effect of Chicago's community policing program (a community-wide intervention) on neighbourhoods' crime rates, model the potential outcomes in any local area as a function of the treatment assignments of all the other units within the framework of a generalized linear model with spatially auto-correlated random effects. Sobel (2006), estimating the treatment effect of the Moving To Opportunity (MTO) program, shows the possible consequences of a violation in the SUTVA by the definition of different causal ”estimands” of interest. The aforementioned author, allowing for the presence of interferences between participants, estimates a non-zero impact on the potential outcome of the untreated (no impact in the case in which the SUTVA still holds).
Arpino and Mattei (2013), considering interactions between units but assuming the validity of the SUTVA between different groups (in their case sector of activity), propose a measure of proximity based on a function of firms' characteristic, like geographical distance between firms and firms' size. To resume, the feature that links these works is the evaluation of the presence of indirect effects through the comparison of appropriate treated and control groups. In this way it is possible to approximate the presence of interferences between units with a predetermined measure of proximity and, relaxing SUTVA hypothesis, identify the impact of the interactions on causal effect.
An alternative approach to address SUTVA violation is proposed by Manski. Manski (1993) explains how the impossibility to distinguish between endogenous and contextual interactions and the possibility of correlated effects reveals the so-called "Reflection Problem"[11]. Manski refers to endogenous effect as the contemporaneous and reciprocal influences of peers, whereas the contextual effect includes measures of peers unaffected by current behaviour.
Identification problem arises because mean behaviour in the group is itself determined by the conducts of group members, i.e. data on outcomes do not allow to discriminate if group behaviour actually affects individuals actions, or group behaviour is simply the aggregation of individuals conducts. From this perspective, solutions to reflection problem encompass alternative approaches to the linear-in-mean model (Manski, 1993; Brock and Durlauf, 2001; Moffitt, 2001). The set of proposed alternatives aims to separate peer influences in endogenous and contextual effects and includes changes in individual behaviour over the time (lagged vs contemporaneous), non linear function or the introduction of different feature than the group mean behaviour, like the median.
Further developments on this approach involve, among others, the identification of binary choice model with social interaction (Brock and Durlauf, 2007), restrictions on the shape of the response function (Manski (2013) introduces the concepts of Constant Treatment

[11] Manski (2000) : *"The reflection problem is similar to the problem of interpreting the almost simultaneous movements of a person and his reflection in a mirror. Does the mirror image cause the person's movements or reflect them?"*

Response (CTR) and Semi-Monotone Treatment Response (SMTR)) and estimation of structural interaction effects in a social economics context by a spatial autoregressive model (Lee, 2006).
Sinclair et al. (2012) suggest a third way to deal with the violation of the no-interference assumption. In detail, the aforementioned authors, designing a multi-level experiment in which treatments are randomly assigned to individuals and varying proportions of their neighbours, find evidence limited to within-household spillovers (no evidence of spillovers across households). Moreover, they suggest to extend multi-level experiment to a wide branch of application, including what they define as "policy diffusion" (research and development, environmental policies, etc.) and in general to any instances in which the intervention occurred in one location may have an impact on policy outcome in nearby areas.
However, the growing interest on the cases in which the no-interference assumption is violated is not yet supported by the development of a unique theoretical and methodological framework. For these reasons, in the remainder of this dissertation we aim to analyse and recombine the concept of spillovers and spatial proximity into the causal analysis framework[12].

1.3 Spatial interferences and causal effect: a review

Causal inference in presence of interactions both at individual or cluster level makes not possible a straightforward adjustment of the RCM approach. Notwithstanding, major efforts are devoted to analyse a methodological framework which enables to address the challenges related to the presence of interferences between units. In this section, starting from the identification problem defined by Manski (1993), we propose a methodological review of the different approaches developed in literature. In more detail, we will focus on spatial and hierarchical methodologies to examine the relationship, and the related issue, between spatial interferences and causal effects.
The so-called ”Reflection Problem” fully summarize the fundamental identification problem when interferences has been taken into account. Manski (1993), considering the occurrence of endogenous and exogenous effects and their implications on the overall neighbourhood effect, highlights the intractable identification of causal impacts. From a methodological perspective, the "Reflection Problem" takes the form in 1.1:

$$\begin{aligned} y_i =& \rho_1 E[y_i|a] + x_i^{'}\beta + E[x_i|a]\gamma + v_i \\ v_i =& \rho_2 E[v_i|a] + u_i \end{aligned} \tag{1.1}$$

[12] However, in this chapter the analysis is limited to the study of existing literature of causal inference in presence of interferences. The development of a theoretical and conceptual framework able to estimate both direct and indirect effects of the policies is explained in next chapters.

y_i is the outcome of interest, x_i a vector of exogenous variables, u_i and v_i are unobservable error terms, while the variable a indicates the location. This specification allows to distinguish three different sources through which neighbours can influence the outcome of a unit: ρ_1 captures endogenous effects (i.e. the outcome of an individual depends on the outcomes of other individuals belonging to his neighbourhood), γ indicates the exogenous effects (i.e. the impact of the mean group characteristics on individual outcome) and ρ_2 the correlated effects of unobserved that affect agents in location a.
Using the law of iterated expectations and substituting $E[v_i|a]$ we can rewrite 1.1 as follows:

$$y_i = (\rho_1 + \rho_2 - \rho_1\rho_2)E[y_i|a] + x_i^{'}\beta + E[x_i|a](\gamma - \rho_2\beta - \rho_2) + u_i \qquad (1.2)$$

Equation 1.2 shows that the parameter on $E[yi|a]$ is a mixture of both endogenous and correlated effects. In other words, ρ_1 and ρ_2 cannot be identified separately without data on v_i. Taking the expectations of 1.1 and, given the observable characteristics, rearranging the terms gives the reduced form of 1.1:

$$y_i = x_i^{'}\beta + \frac{\rho_1\beta + \gamma}{1-\rho_1}E[x_i^{'}|a] + \frac{\rho_1}{1-\rho_1}E[v_i|a] + v_i \qquad (1.3)$$

Equation 1.3 demonstrates that only β and the composite parameter $\frac{\rho_1\beta+\gamma}{1-\rho_1}$ are identified, even when there is not spatial autocorrelation in the unobservables ($\rho_2 = 0$). This assumption implies that is possible to identify only the overall effect of neighbours' characteristics.
Spatial econometrics can allows to address, at least partially, the reflection problem (Gibbons and Overman, 2012). These authors consider a data generating process analogous to 1.1 and 1.3:

$$y_i = \rho_1 w_i^{'}y + x_i^{'}\beta + w_i^{'}X\gamma + v_i \qquad (1.4)$$

$$y_i = x_i^{'}\beta + w_i^{'}X\frac{\gamma + \beta\rho_1}{1-\rho_1} + \frac{\rho_1}{1-\rho_1}w_i^{'}v + v_i \qquad (1.5)$$

where w_i is the spatial weight vector able to generate "neighbourhood averages" of the estimates of $E[\cdot\,|a]$ and ρ_1 represents the effect of the observed mean neighbourhood outcome of the sample. In spatial econometrics, the specification in 1.4 (resp. 1.5) is identified as a Spatial Durbin (SD) (resp. Spatial Lagged of X with spatial autocorrelated error term (SLX)) model. Repeated substitution of y in 1.5 leads to 1.6:

$$y_i = x_i^{'}\beta + w_i^{'}X(\beta\rho_1 + \gamma) + \rho_1 w_i^{'}WX(\beta\rho_1 + \gamma) + \rho_1^2 w_i^{'}W^2X(\beta\rho_1 + \gamma) + \cdots + \omega_i \qquad (1.6)$$

In equation 1.6 all causal parameters are identified, i.e. there are only three parameters to estimate and an infinitely large number of spatial lags of x_i. Nevertheless, spatial econometricians solve the "Reflection Problem" making possible the identification of the causal effects, critics are moved on the construction of the matrix **W**. It, representing real-world linkages, needs to be defined a-priori. The hypothesis on **W** creates a clear distinction between "spatial" and "social" viewpoints. Indeed, social scientists does not agree on an a-priori knowledge of **W**. This branch considers that **W** is almost always never known but can be considered only as a good approximation of $E[\cdot\,|a]$. In other terms, social analysis requires more structure to address the identification of causal effects in presence of interferences.

An alternative solution to the reflection problem can be found in hierarchical model (HLM) (Lee, 2006; Lee et al., 2010). Recently, HLM becomes increasingly popular especially in economic geography, where the presence of a hierarchical structure (for example: local, regional and national) can determine multilevel effects on the outcome. Moreover, this approach allows to check the occurrence of additional spatial effects at different levels of a nested hierarchy, i.e. the effects of being located within the same region.

Understanding the role played by different form of interactions between variables which can affect each units of the system and/or the group they belong to has important empirical implications. Indeed, independently from the presence or not of spatial autocorrelation, the assumption of independence is usually incorrect when data are extracted from a population with a grouped structure since this adds a common element to otherwise independent errors, thereby inducing correlated within group errors.

Following the example in Corrado and Fingleton (2012) is possible to link spatial econometrics with HLM approach by the inclusion of general form of network dependence between individuals belonging to the same group. In this way the aforementioned authors are able to rewrite a spatial autoregressive model (SAR) as in 1.7:

$$\mathbf{Y} = \beta_0 + \rho\mathbf{W}\mathbf{Y} + \mathbf{X}\beta_1 + \mathbf{Z}\gamma + \mathbf{u} + \mathbf{e} \tag{1.7}$$

with **Z** a $N \times q$ matrix of contextual variables defining group characteristics and **W** a block matrix such that 1.8.1 and 1.8.2 are verified:

$$\mathbf{W} = Diag(\mathbf{W}_1, \cdots, \mathbf{W}_g) \tag{1.8.1}$$

$$\mathbf{W}_g = \frac{1}{w_j}(\iota_{w_j}\iota_{w_j}^{'}) \tag{1.8.2}$$

where ι_{w_j} is a w_j dimensional column vector of ones. The specifications in 1.7, 1.8.1 and 1.8.2 allow to examine an HLM where individuals within the same group are affected in the same way by other unit in the group. In this way is possible to focus on within-group effects assuming that $\overline{Y_j} = \frac{1}{w_j}\sum_{i=1}^{w_j} Y_{ij}$, i.e. all the individuals in group i have same weight. This implies that interactions between individuals do not spill across group boundaries and their intensity is not a function of the distance, but depend on the belonging or not to a predetermined group. Under this assumption we can rewrite 1.7 as in 1.9:

$$Y_{ij} = \beta_0 + \rho\overline{Y_j} + \beta_1 X_{ij} + \gamma Z_j + \epsilon_{ij} + u_j \tag{1.9}$$

Where, following the line of reasoning in Manski (1993), β_1 is the effect of individual characteristics, ρ the strength of endogenous group effect, γ captures exogenous effect, u_j random group effects and ϵ_{ij} an individual specific random component. The reflection problem is expressed simply by taking group means of both sides in 1.9. Resolving for $\overline{Y_j}$ and assuming $\overline{X_j} = Z$, we obtain 1.10:

$$Y_{ij} = \frac{\beta_0}{1-\rho} + \frac{\beta_1 + \gamma}{1-\rho}\overline{X_j} + \beta_1(X_{ij} - \overline{X_j}) + e_{ij} + u_j^{'} \tag{1.10}$$

with $u_j^{'} = u_j + \rho\frac{\overline{e_j}+u_j}{1-\rho}$. The reduced form in 1.10 implicitly includes the hypothesis of reflection $\overline{X_j} = Z$, even if makes not possible to identify the structural form in 1.7. The identification problem can be resolved including in the model the presence of inter-group effect. Assuming $\overline{Y_l}$ be the mean of the responses of neighbours areas and $\overline{Z_l}$ the inter-group contextual effect, model 1.9 becomes:

$$Y_{ij} = \beta_0 + \rho_1\overline{Y_j} + \rho_2(\overline{Y_j} - \overline{Y_l}) + \beta_1 X_{ij} + \gamma(Z_j - \overline{Z_l}) + \epsilon_{ij} + u_j \tag{1.11}$$

Corrado and Fingleton (2012) suggest to consider spillover variables in terms of deviations, both with reference to endogenous inter-group one $(\overline{Y_j} - \overline{Y_l})$ and contextual, or exogenous, spillovers $(Z_j - \overline{Z_l})$. Considering the average relationship in 1.11 and resolving for $\overline{Y_j}$ we are able to obtain:

$$\begin{aligned}\overline{Y_j} =& \frac{1}{1-\rho_1-\rho_2}[\beta_0 + \beta_1\overline{X_j} + \gamma(Z_j - \overline{Z_l}) - \rho_2\overline{Y_l}] + u_j^{'}\\ u_j^{'} =& \frac{1}{1-\rho_1-\rho_2}(\overline{\epsilon_j} + u_j)\end{aligned} \tag{1.12}$$

Substituting 1.12 in 1.11 and rearranging the terms, we can rewrite the model:

$$\begin{aligned}\overline{Y_j} =& \frac{\beta_0}{1-\rho_1-\rho_2} + \underbrace{\beta_1(X_{ij} - \overline{X_j})}_{\text{within-group exogenous}} + \underbrace{\frac{\beta_1}{1-\rho_1-\rho_2}\overline{X_j}}_{\text{between-group exogenous}} - \underbrace{\frac{\rho_2}{1-\rho_1-\rho_2}\overline{Y_l}}_{\text{inter-group endogenous}} + \\ & \underbrace{\frac{\gamma}{1-\rho_1-\rho_2}(Z_j - \overline{Z_l})}_{\text{inter-group contextual}} + \epsilon_{ij} + u_j^{''}, \qquad \text{with} \qquad u_j^{''} = u_j + (\rho_1 + \rho_2)u_j^{'}\end{aligned} \tag{1.13}$$

In this way, we demonstrate that an HLM as in 1.13 can facilitate the identification of the parameter in 1.9, i.e. the inclusion of inter-group effects allows to estimate causal effect. The model in 1.13, for ease of interpretation, can be considered as a general form that does

not consider directly the "Reflection Problem"[13].
More general form of interactions, including the ones based on the geographical proximity, are easily implemented by 1.13 giving structure to inter-group effects, i.e. it is sufficient to consider the relationship between groups on the basis of a correctly defined block diagonal matrix **W**. Corrado and Fingleton (2012) explain how the inclusion of spatial effects avoid the omitted variable problems that can arise with endogenous spatial lag model and allows to identify causal effects in presence of interaction.
The focus on multilevel aspects of causal effects, with the combination between spatial econometrics methods and HLM, constitutes a powerful tools to address the "Reflection Problem". Moreover, this approach allows to estimate consistently the presence of spillover that arise with the geographical proximity between units. Some early application of the use of HLM combined with spatial econometrics to address the problem of interference are found in Elhorst and Zeilstra (2007) and Burridge et al. (2014).
Vanoutrive and Parenti (2009) try to build a theoretical framework to the use of HLM in a spatial setting, built on a modified version of the First Law of Geography Tobler (1970)[14]. The aforementioned authors, proposing a comparison between HLM and spatial econometric techniques, discuss the possibility to combine the two approaches. But, as Shakespeare says in its Merchant of Venice "*All that glisters is not gold*".
Anselin (2002) admonishes about the presence of side effects in the use of spatial hierarchical model. Moreover the use of a block diagonal matrix that assigns the same weight to each unit belonging to considered group[15] is reasonable only when the number of units is limited, i.e. when $n_g \to \infty$ the contribute of every unit in the group is equal to 0. Another consequence of the combination between hierarchical model and spatial proximity is the increment of the complexity of the analysed model. The further complication intrinsic to spatial hierarchical model may imply a difficult interpretation of the estimated parameter (Langford et al., 1999).
Gibbons et al. (2014) devote an entire paragraph to explain why cluster randomization does not solve the reflection problem. They concord on the hypothesis that the presence of inter-group effects allows to identify causal parameters, as explained in 1.13, even if it is still not possible to estimate separately the parameter of the structural form 1.11. Moreover, the implicit assumption under cluster randomization is the presence of endogenous group membership and/or omitted group specific variables that can affect the outcome. Both assumptions unveil the occurrence of correlated characteristics between individuals belonging to same group. The aforementioned authors demonstrate how within-group correlation, both in terms of observables or unobservable characteristics, have detrimental

[13]The results in presence of reflection are similar (Corrado and Fingleton, 2012).
[14]*"Everything is related to everything else, but things in the same region are more related than things in different region"* (Vanoutrive and Parenti (2009) on Tobler's First Law of Geography).
[15]Remind that every unit in the group has weight equal to: $w_g = \frac{1}{n_g}$.

effects on the effective sample size, i.e. sample size depends on the size of within-group correlation and the average group size. More in detail, when within group correlation is equal to 1 the effective sample size corresponds to the number of the groups, whereas if within group correlation is equal to 0 sample size coincides with the total number of units in the groups. Every intermediate situation gives standard errors too large or too small if the inference is based, respectively, on the number of group or individuals. The concerns over inference are, at least partially, addressed in the case in which researcher has control over group membership and in presence of random assignment of the units to treated and control groups[16].

Gibbons et al. (2014) propose an in-depth analysis for the case of spatially auto-correlated unobservables correlated with the observables characteristics. They avoid to consider the presence of endogenous interaction, focusing on the model:

$$Y = X\beta + W_X X\theta + W_Z Z\gamma + W_v v\lambda + \epsilon \tag{1.14}$$

The specification in 1.14 allows to distinguish between interaction at individuals level, between groups and on unobservable characteristics by the inclusion of the three different weight matrices W_X, W_Z and W_v. In case like the one depicted in 1.14, spatial unobservables can be omitted simply pre-multiplying both sides of the equation for $[I - W_v] \iff plim(W_v - W_v W_v)v = 0$. In other words, if the necessary and sufficient condition is satisfied, spatial unobservables can be removed just applying a spatial difference, i.e. all variables are transformed subtracting the spatial mean of the unobservables. Under the assumption $W_X = W_Z = W_v = W$, applying the spatial difference of 1.14 produces:

$$Y - WY = (X - WX)\beta + \xi, \quad \text{with} \quad \xi = \epsilon - W\epsilon \tag{1.15}$$

Specification in 1.15 removes both spatial interaction at individual and group level, making impossible the identification of the parameters θ and γ. The estimation of the parameter on the spatial observables is possible only under the strong assumption of different structures of connection for the observables and unobservables. Duranton et al. (2011) suggests to combine IV and spatial differencing in the case in which imposing different weight matrices between observables and unobservables is not preferable, or possible[17]. This approach is valid even when the instruments are orthogonal to the spatial unobservables.

Gibbons et al. (2014) consider also the case in which group membership is endogenous. Under this hypothesis the identification become more and more complex compared to the previous case. Social network literature proposes different methodologies in order to deal

[16] This is an alternative assumption to the random assignment of treatment to all members of existing groups.

[17] The possibility of different connection structure are directly considered in Boundary Discontinuity Design. This methods corresponds to a spatial case of RDD and the researcher can impose that administrative boundaries create discontinuities just on the way in which observable characteristics can vary over the space.

with endogenous group membership, including Bayesian inference, frequentist approach and a group-level correction term. However, this approaches are not yet explored in a spatial econometric framework.

1.4 Conclusions

The idea behind this chapter is to recombine the concept of diffusion of knowledge spillovers under the rigorous framework of policy evaluation. A clarification on the relationship between the two fields can be partially retrieved with the development of a new wave of place-based policies, by means of which government aims to develop regional strengths and the creation of connections between core and peripheral areas. However, the inclusion of the concept of knowledge spillovers in the standard RCM is not straightforward. Indeed, RCM model relies on the SUTVA hypothesis. This assumption directly excludes the occurrence of interactions (also known as interferences) between units.

In recent years many researchers has worked on the construction of an alternative methodological framework in which can be possible to estimate both direct than indirect effects, but the literature is still scarce and fragmented. Different approaches have been developed and tested, including the comparison of ad-hoc estimand groups, multi-level analysis and alternative hypothesis replacing the SUTVA. The inclusion of interactions makes not possible the estimation of the causal effects, i.e. Manski (1993) argued that this situation conduct to the so-called "Reflection Problem", a case in which is not possible to distinguish between endogenous and contextual effects.

This case, and the related identification problem, is of primary relevance in a wide variety of fields, including infection diseases, sociology, education, regional and urban economics. The development of spatial and social methodologies has a twofold relevance in the literary debate over causal inference. From one hand, spatial and social researchers has assumed a primary role in causal analysis in presence of spatial and/or social interaction. From the other hand, these methodologies provides the ”optimal” solution to the problem of causal identification (see Section 1.3).

In other words, spatial econometrics and network theory are built under the hypothesis that the outcome of a unit depends not only on its own characteristics, but is a function of the realized outcome and/or the characteristics of spatial and social neighbours. In this way, these approaches make clear the connection between the occurrence of interactions and causal effects. However, this thesis aims to analyse the actual state of art from a spatial viewpoint.

From this perspective, some preliminary works propose to address the identification problem through Spatial, Hierarchical or other methodologies that combine both a-spatial and spatial approach. Notwithstanding, the primary relevance of causal analysis in presence of interferences, both from government and academic viewpoints, is not yet completely supported by the development of an homogeneous framework.

The aim of this chapter, and more broadly of the entire thesis, is the development of possible solutions to the issues related to the inclusion of interactions between units in causal inference. In detail, in the remainder of this thesis we propose two distinct DID approaches. The first, presented in Chapter 2, is framed in the context of observational studies. In this paper we develop an approach similar to Cerqua and Pellegrini (2014).

These authors propose a partially relaxed version of the SUTVA that take into account the interactions between the untreated firms; they distinguish non recipient firms considering their exposition to the subsidized ones and evaluate the spillover effects by a comparison between the affected ones and the others. The peculiarity of our approach is to assume the validity of the SUTVA only outside the groups, in relation to their geographical localization, while we allow the presence of interactions within the groups.

The second proposed approach, explained in Chapters 3 and 4, combines both spatial and hierarchical model. Following Corrado and Fingleton (2012), this approach allows to decompose the total causal effect in both direct and indirect impacts. The presence of interferences is modelled by the state of the treatment of the neighbours units and directly included in the regression model of the SH-DID (Spatial Hierarchical Diff-in-Diffs). This approach demonstrates the correctness of the ATE even in presence of spatial interferences. However, our analysis is limited only to first order linear interactions between units, avoiding to consider the presence of additional causal effects due to higher order neighbours. In addition, the SH-DID allows to check the spatial dimension of both direct and indirect effects by changing the spatial weight matrix (see, as an example, Chapter 4).

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Chapter 2

Are Regional Policies effective? An empirical analysis on the diffusion of R&D incentives[1]

In recent years, regional R&D policies have an increasingly relevant role in stimulating innovation. Moreover, EU strategy aims to foster a *"smart, sustainable and inclusive growth"* in less developed areas by means of innovation policies oriented to the identification and development of correct areas of specialization. The scope is to promote growth in areas characterized by comparative advantages and the formation of network externalities (Foray et al., 2011).
In this context, increasing regional policies efficiency becomes fundamental. In detail, public instruments have to be efficient in providing public goods, controlling public expenditure and, in particular, closeness to citizens preferences. The strengthening of regional policies as tools to enhance innovation and growth has a twofold justification. A stream of literature highlights how "place-based" policies, supported by institutional reforms and well-informed local governments, stimulate the commitment of the stakeholders with beneficial effects on local development and, potentially, on the entire economic system (Barca, 2009; OECD, 2009b; Garcilazo and Oliveira Martins, 2015).
Crescenzi and Rodríguez-Pose (2011) propose a conceptual framework to justify "place-based" policies. Under their perspective, regional policies is considered a vehicle for local development and an instrument for coordinating different type of policies both at national and regional level. The second theoretical justification is based on the wide heterogeneity between different regional contexts.
This approach aims to increase the links between developed areas and peripheral regions in

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order to maximize knowledge spillovers and, in wider terms, innovation[2](OECD, 2009a). Overall, ”place-based” policies tend to emphasize the role played by public administrations. Their intervention includes, but it is not limited to, the provision of the incentives. Indeed, policy-makers have to identify the locations where regions have comparative advantages and recognise the possibility of investments in backward areas (Foray, 2009).

In this paper we evaluate the effectiveness of a broad range R&D regional policy in Umbria, a small region located in Central Italy. The development of a ”place-based” approach allows to assess the ”additional” impact of public policies promoting R&D activities of the firms, taking into account regional areas of specialization. Our approach focuses on the creation of spillovers in response to the relative geographical and economic proximity of the firms. We restrict the analysis only to the effects of regional policies, controlling for the presence of any national and EU incentives.

The most relevant Italian empirical literature on R&D subsidies provides contradictory indications. Indeed, while some evaluation studies demonstrate a positive impact of the incentives, with a greater efficacy limited to the SMEs (Merito et al., 2007; Bronzini et al., 2008), many others show no additionality (Accetturo and de Blasio, 2008; De Blasio et al., 2015; Andini and De Blasio, 2016). Moreover, Bronzini and de Blasio (2006) attribute additionality to a process of inter-temporal substitution that leads companies to anticipate investment in R&D.

Despite the wide and heterogeneous literature on empirical analyses at national scale[3], works focused on the evaluation of regional innovation policies are still scarce. Gabriele et al. (2007) and Corsino et al. (2012), analysing the case of Trentino-South Tirol, underline an increment on the stock of capital with beneficial effects on the access to new market opportunity, even if not fully captured on factor productivity and profitability.

Fantino and Cannone (2014) provide evidence on the effectiveness of regional policies as instruments able to foster short term investments, especially for the smallest firms and the ones with a low credit rating. Bronzini and Iachini (2011), examining R&D incentives in Emilia-Romagna, show additionality limited to SMEs investments. This result is in line with Bronzini and Piselli (2016). These authors provides evidences on a significant and positive impact on the number of patents of small firms. Overall, literature suggests to take into account firms dimensions. Therefore, in this paper we will provide distinct estimates on total and SMEs sample.

This chapter introduces two distinct innovations. The main innovations of this work concern two particular aspects related to the methodological approach and the dataset used. The first novelty, more methodological, consists in the evaluation of the global effect of the policies. This operation requires the identification of spillover effects. Therefore, we allow for

[2]For further information on the topic see Krugman and Venables (1995) and Fujita et al. (2001) intra alia.

[3]For further information on evaluation studies at national scale see the surveys in David et al. (2000), Hall and Van Reenen (2000), Cerulli (2010) and Zúñiga-Vicente et al. (2014).

differentiated interactions between the firms on the basis of their geographical localization and market concentration by the development of a ”novel” DID approach.
The second crucial point concerns the typology of data used in estimating treatment effects. Indeed, the regional Core of Evaluation and Verification of Public Investments has made available CIS micro-data[4]. Despite the relevant amount of informations included in the CIS and the easy comparability with the results of studies involving other European countries, this data is, actually, used only by a limited number of works to evaluate the effects of public policies (Cefis and Evangelista, 2007; Cerulli and Potì, 2008; Marzucchi and Montresor, 2013; Becker and Bizer, 2015).
Nevertheless, this chapter is the first, to the best of our knowledge, which merges the micro-data of the CIS with balance sheet data and a questionnaire administered by the Regional Public Administration of Umbria. This operation makes possible to obtain complete and detailed information on technological structure, R&D process, economic and financial situation of the firms.
The remainder of the chapter is organized as follows. Second section proposes a detailed analysis of the data, including a description of the characteristics of the policies and the firms considered; third section introduces the proposed methodological framework with a focus on the distinction between traditional and our novel approach. In fourth section we present the results of the estimates, whereas the last section is devoted to test the validity of the common trend assumption in order to confer robustness to our results. Conclusions and policy implications are at the end of the chapter.

2.1 Data Analysis

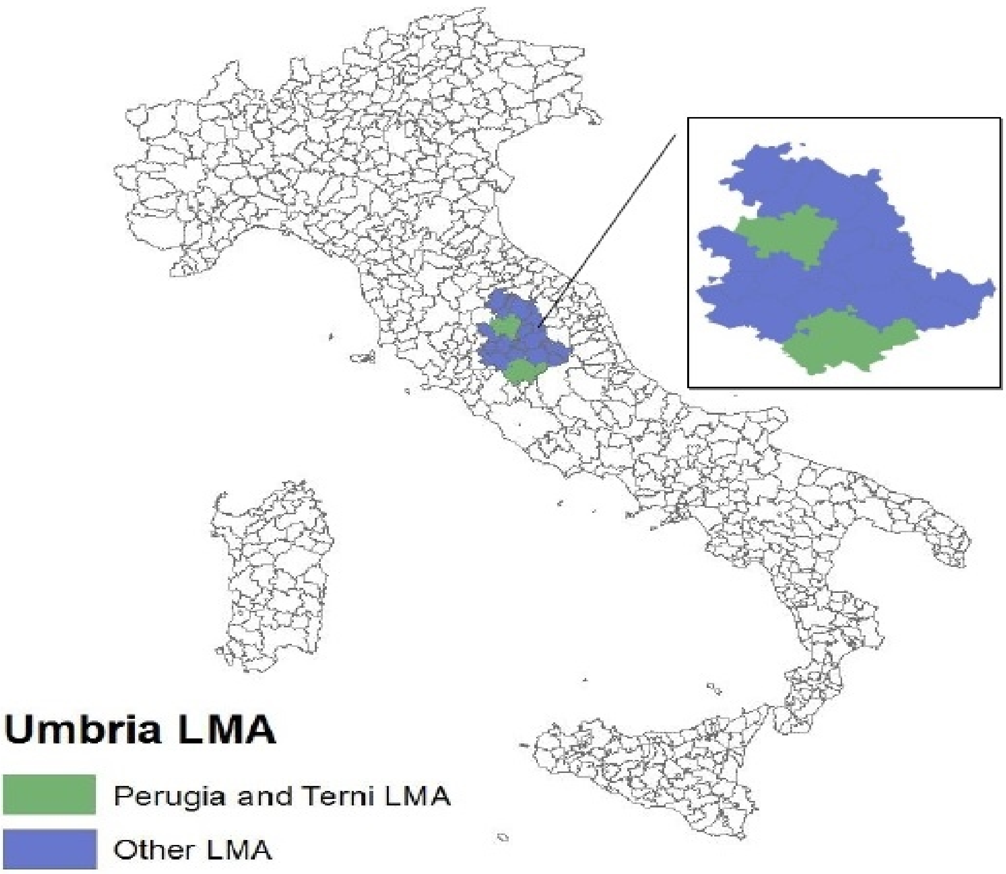
Labour Market Areas

This chapter focuses on the evaluation of place-based policies in Umbria, a small region located in Central Italy. A place-based approach requires a preliminary definition of the correct functional subdivision of regional territory. Considering the limited geographical dimension of this region we cannot take into account the traditional administrative division of the territory, like municipalities or provinces. Indeed, taking into account the presence of relevant demographic and economic agglomeration, we decide to use a more functional subdivision which enables to identify developed local areas.

[4]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. The CIS provides statistics broken down by type of innovators, economic activities and size classes (Eurostat).

For this reason, the territorial grid that best suits the purposes of this study is based on the Labour Market Areas[5] (from now LMAs). Umbria Region is composed by 14 LMAs, many of which characterized by a reduced size which does not allow to fully grasp the presence of externalities. Figure 2.1 highlights two distinct issues. On one hand, it contextualizes

Figure 2.1. Italian Labour Market Areas



Legend: Geographical distribution of Umbria LMAs in the overall Italian context.

the limited regional dimension of Umbria in the overall Italian extension. On the other hand, looking at regional LMAs distinguish between main (Perugia and Terni) and the other LMAs. The definition of the more developed local areas is discussed in Table 2.1.

Notwithstanding the limited average dimension of regional LMAs, Table 2.1 allows to identify the occurrence of two major areas, Perugia and Terni, where population and

[5] Labour market areas (LMAs, "local labour systems" or Sistemi Locali del Lavoro) are sub-regional geographical areas where the bulk of the labour force lives and works. They respond to the need for meaningfully comparable sub-regional labour market areas for the reporting and analysis of statistics. LMAs are defined on a functional basis, the key criterion being the proportion of commuters who cross the LMA boundary on their way to work (ISTAT). An important characteristic of the LMA is that the areas are not overlapping and cover the entire region.

Table 2.1. Umbria Labour Market Areas

Denomination	Population	Employed	N. of jobs	Internal Movements	Demand	Offer	Municipals
ASSISI	57640	20698	20269	14934	0.74	0.72	4
CASCIA	6489	2029	1825	1635	0.90	0.81	4
CASTIGLIONE	24955	8022	7073	5132	0.73	0.64	3
CITTÀ DI CASTELLO	56075	20477	19496	16643	0.85	0.81	4
FOLIGNO	85262	28145	26743	22145	0.83	0.79	6
GUALDO TADINO	31476	9689	8407	6824	0.81	0.70	6
GUBBIO	33874	11095	10038	8883	0.88	0.80	2
NORCIA	7934	2376	2426	1959	0.81	0.82	4
PERUGIA	243653	87072	91796	77890	0.85	0.89	9
SPOLETO	45688	14713	15253	12470	0.82	0.85	6
TODI	37854	11611	10527	8278	0.79	0.71	7
UMBERTIDE	20326	6973	7001	4980	0.71	0.71	3
ORVIETO	42983	13461	12801	11166	0.87	0.83	12
TERNI	178862	57036	55633	52020	0.94	0.91	18

Source: Quality Indicator of Umbria LMAs (Istat, 2011)
Legend: The table shows demographical and economic variables of Umbria LMAs. In detail with Employed and Number of jobs we indicate respectively the total number of people which lives or works in the LMAs. The internal movements represents people that lives and works in their own LMAs. The demand (offer) column represents the ratio between internal movements and Resident Employed (Number of Jobs).

industrial production tend to be more agglomerated. For this reason, the localization in one of the main LMAs may cover a determinant role in evaluating the effectiveness of regional policies. Starting from this assumption, we will take into account the location in one of the main local areas to analyse the role played by industrial concentration on R&D processes and technological spillovers.

Dataset

Since the 6th Framework Programme (FP6, 2000-2006) Umbria Region has implemented a series of strategic actions to sustain the creation of business networks and improve their links with research centres. From 2004 the measures implemented by the Region to encourage entrepreneurial and territorial competitiveness are included in the so-called ”competitiveness package”.

In this analysis, we take into account only the incentives directly provided by the Region. This choice has a twofold relevance. On one hand, it allows to assess the additionality of "place-based" policies on technological and economic performances of the firms. On the other hand, this chapter contributes to enhance the lack of studies at regional level.

Moreover, this procedure allows to consider the rankings of three distinct instruments: calls for investment in technological innovation, Law N. 598/1994; calls for integrated packages of benefits (Pacchetti Integrati di Agevolazioni, PIA); calls to promote the creation of stable networks of enterprise (Re.Sta.). The Regional Administration, in the period between 2004 and 2009, provided over €120 millions to the businesses for an aggregate number of 14 calls. Taking into account the presence of more than one ranking in some calls, we have observed a total amount of 17 announcements.

Notwithstanding, the substantial commitment of regional policy-maker (see Table 2.2) is not supported by a corresponding involvement of the firms on public funding opportunities.

Table 2.2. Number of funded projects per announcement

Announcement	N. projects funded	Overall funding	R&D funding
RESTA 2007	15	1457578,00	432330
RESTA RICERCA 2007	69	9519585,91	2992390
RESTA INNO 2007	64	4055531,75	0
RESTA INNO 2008	28	2825527,69	0
RESTA RICERCA 2008	37	3922551,49	2520110
RESTA MODA 2009	32	981168,74	0
RESTA RICERCA 2009	43	5960491,60	3319415
PIA 2004	37	5313662,50	1781310
PIA 2006	47	6637302,39	2038105
PIA 2007	187	27672951,00	4572935
PIA RICERCA 2008	56	10156096,31	6478780
PIA INNO 2009	45	7036431,71	0
L. 598/94 2004	32	6701330,00	6701330
L. 598/94 2006	41	6407565,00	6407565
L. 598/94 2007	74	10021750,00	10021750
L. 598/94 2008	49	6660275,00	6660275
L. 598/94 2009	59	9088240,00	9088240
TOTAL	915	124418039,08	63014535

Source: Core of Statistics and Evaluation of the investment, Regione Umbria.

Legend: This table resumes the overall financial commitment of the Region to the SMEs in order to improve their competitiveness, pointing out the number of funded projects for each announcements. In the last column is reported the incentives devoted directly to R&D activities.

In fact, even though individual calls have funded all the projects on the list, the analysis of the participation rate of the firms (number of calls on which each firm has obtained funding) shows that the majority of them have participated in a single call; which very few are the companies funded on more than 3 calls.

Regional economic burden to enhance regional competitiveness makes possible the financing of 915 projects. However, the aim of this chapter is focused only the effectiveness of public aid directly devoted to foster R&D activities. In this way, we have isolated 480 funded projects carried out by 253 companies for a total contributions of €63 millions. The 253 financed firms constitutes the factual sample.

Table 2.3. Summary of public policies by objective

	Aid for competitiveness (1)	Aid for R & D activities (2)
N. Public announcement	17	14
N. Financed Firms	575	253
N. Financed Projects	915	476
Total contributions	124418039,08	63014535

Source: Core of Statistics and Evaluation of the investment, Regione Umbria

Legend: Resume of policies implemented by Umbria between 2004 and 2009. Column (1) reports the overall amount devoted to foster territorial competitiveness, Column (2) selects only the firms that receive incentives to R&D activities.

On the other hand, the counterfactual sample is constituted by 148 companies selected through the method of the matching pairs. The criteria for selecting control units consider: the number of employees, turnovers, the economic sector, the business location, profitability ratios. In this way, we obtain a final dataset composed by 401 firms.
The definition of outcomes able to furnish detailed information on economic and financial accounts and on the main characteristics of the production process, in particular those related to innovation and investments in R&D has required the merging of data from different sources. The economic and financial accounts are considered by the balance sheet data, provided by the Infocamere archives, for the years between 2004 and 2011. Informations on technological processes are extracted from the questionnaire[4] and the micro-data of the Istat annual survey (i.e. CIS) on R&D. Besides, CIS data allow to identify pairs of companies subsidized and non supported on the basis of their propensity to innovate.
To provide evidence on the absence of structural pre-treatment differences between treated and control we summarize the main economic indicators referred to the baseline year (2005).

Table 2.4. Summary Statistics

	Treatment	Mean	Std. Err.	[95% Conf.	Interval]	Difference in Means
Turnover	0	12996575	2740826	7556794	18400000	4128271
	1	8868304	1752325	5408279	12300000	[3102912]
Employees	0	53.5	6.5	40.7	66.3	4.2
	1	49.3	5.8	37.8	60.8	[9.1]
Capital assets	0	4576935	1338821	1919747	7234123	1722595
	1	2854341	554093	1760314	3948367	[1255488]
Intangible assets	0	753746	470290	-179649	1687140	464352
	1	289393	67183	156745	422042	[371326]
Net assets	0	9471459	1746489	6005161	12900000	3741262*
	1	5730197	897238	3958649	7501744	[1778125]
ROE	0	0.28	0.35	-0.42	0.98	-0.52
	1	0.81	0.38	0.06	1.56	[0.56]
Ebitda	0	949779	219093	514939	1384619	155031
	1	794748	128246	541522	1047975	[237002]
ROI	0	2.65	0.66	1.33	3.96	-2.35*
	1	5.00	0.81	3.39	6.61	[1.17]
Added Value	0	2435978	385156	1671551	3200405	340545
	1	2095433	303563	1496037	2694830	[493224]
Added Value per Employee	0	40635	3272	34142	47129	-14784
	1	55420	11745	32228	78611	[15413]
Turnover per Employee	0	231696	46494	139418	323974	-60602
	1	292298	97795	99190	485406	[131597]

Legend: This Table resumes economic and financial characteristics for baseline year (2005), differentiated by state of treatment. Reported statistics are for variables in the numeric format of the data source. The column "Difference in Means" reports the difference between the average of control and treatment group, meanwhile the standard errors are indicated in square bracket. The presence of significant differences between the two samples is evaluated by way of a mean comparison test. The level of statistical significance of the test is indicated with: * 0,05 , **0,01

Table 2.4 highlights the different economic structure between treated and controls. The firsts exhibit, in average, better results on the profitability indicators (ROE and ROI). On the other hand, the untreated show greater values on turnovers, mean number of employees and net

[4]The questionnaire is administered by the Umbria Center of Statistics and Evaluation of the investments and provide precise indications on the dynamics of innovation and research processes. In addition this information allow to take into account the degree of satisfaction of the enterpreneurs on Public Administration actions.

assets.
To check the presence of significant discrepancies between the two samples we have implemented a mean comparison test. This test confirms the absence of structural differences in the baseline period. Systematic differences are found in terms of net assets and ROI; this result, by itself, does not bias the estimates of the difference-in-difference, but requires an additional robustness check. This step is necessary to evaluate if these discrepancies can affect the validity of the ”common trend” assumption. In the next section we present the ”standard” DID and our ”novel” approach. This method, taking into account geographical localization, allows for differentiated effects on the basis of firms concentration.

2.2 Methods

In this chapter, we estimate the effectiveness of regional policies by a Diff-in-Diff estimator [6] under the traditional ”counterfactual” framework. This approach is used to estimate the effect of a treatment to measure the differences, between the treatment and control group, of the changes in the outcome variable that occur over time. In other terms, DID evaluate the impact of a policy by a "double difference", in time (pre-post treatment) and between subjects (treated and control). However, the validity of this approach requires un-testable assumptions. Indeed, the results of methodologies based on single difference are characterized by the *"selection bias"*.
On the other hand, if what differentiates treated and controls does not change over time, the Diff-in-Diff eliminates the selection bias and produces correct estimates of treatment effect (parallel trend assumption). In other words, in DID approach differences between the groups are constant over time; thus, without treatment, there would not be differences in behaviour between the groups. To guarantee the accuracy of the DID estimate, the composition of individuals of treated and control groups is assumed to remain unchanged over time.
DID approach is estimated by running a regression analysis of the type:

$$y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 (D * t) + \varepsilon \tag{2.1}$$

where y denotes the outcome, D and t are dummy variables equal, respectively, to 1 for the treated units and for the post-treatment period. Assuming the validity of the SUTVA, we can express the Average Treatment Effects on the Treated (ATT) in terms of ”double

[6] Detailed information on the difference in difference approach and its development can be found in: Ashenfelter and Card (1985); Abadie (2005); Bertrand et al. (2002); Donald and Lang (2007); Athey and Imbens (2006); Puhani (2012); Reggio and Mora (2012).

differences”:

$$\begin{aligned} ATT =&E[y_i|D_i = 1, t_i = 1] - E[y_i|D_i = 1, t_i = 0]- \\ &E[y_i|D_i = 0, t_i = 1] - E[Y_i|D_i = 0, t_i = 0] \end{aligned} \tag{2.2}$$

As already said, a DID model requires two different time periods. This analysis consider a 5 year time window, where t=0 refers to 2005 and t=1 to 2010. The choice of the initial and ending period is related to the years in which regional policies are delivered. Indeed, the great majority of regional public funding is supplied in 2007 and the pre-post treatment periods are correctly defined.

Notwithstanding, this chapter raises a further issue. In detail, applying a ”place-based” approach we aim to identify the occurrence of technological spillovers in response to the combined action of regional policies and business location. The identification of the spillover effects, however, requires a partially relaxed version of the SUTVA hypothesis.

Evaluation strategies based on the SUTVA assumes that the response of a particular unit depends only on its assigned treatment, and not on the treatments received by the others (Rubin, 1974)[7]. There are, nevertheless, circumstances in which invoke the validity of the SUTVA is not plausible. For instance, considering two firms located in the same area and direct competitors and assuming that only one of them receives public incentives, the subsidized one can have an impact even on the other (i.e. the untreated one).

Recently, an increasing number of studies focuses on the cases in which the assumptions at the basis of the SUTVA are violated. Researchers working in this direction shares the common objectives of finding a methodological approach that includes the presence of interactions between units[8]. Nonetheless, research on drawing inference on causal effects in presence of interferences is not yet common, even if some exceptions exist (Verbitsky and Raudenbush, 2004; Sobel, 2006; Rosenbaum, 2012; Tchetgen and VanderWeele, 2010; Hudgens and Halloran, 2012; Kao and Toulis, 2013; Sinclair et al., 2012; De Castris and Pellegrini, 2015)[9].

However, as discussed in Section 1.2 most of the existing works are theoretical and/or focused on randomized experiments. In this chapter we develop an approach similar to the one proposed by Cerqua and Pellegrini (2014). The authors propose a partially relaxed

[7]For a deepening on the no-interferences assumption see Chapters 1 and 3.

[8]Manski (1993) explains how the impossibility to distinguish between endogenous and contextual interactions and the possible presence of correlated effects reveals the so-called "Reflection Problem". The author refers to endogenous effect as the contemporaneous and reciprocal influences of peers, meanwhile the contextual effect includes measures of peers unaffected by current behaviour. The identification problem arises because mean behaviour in the group is itself determined by the conduct of group members. Possible approach in order to take into account the identification problem includes the restrictions on the shape of the response function (Manski, 2013), estimation of structural interaction effects by means of a spatial autoregressive model (Lee, 2006), binary treatment model with ”endogenous” neighbourhood effects (Cerulli, 2015).

[9]New advancements in the field of causal inference using the DID approach in a spatial context are: Chagas et al. (2016),Delgado and Florax (2015) and Di Gennaro and Pellegrini (2016b)

version of the SUTVA that take into account the interactions between the untreated firms; they distinguish non recipient firms considering their exposition to the subsidized ones and evaluate the spillover effects by a comparison between the affected ones and the others.
The peculiarity of our approach is to take into account geographical localization[10] and considering the presence of interactions within the LMAs, i.e. we assume a limitation on the validity of the SUTVA limited to firms located in different LMAs. Therefore, our assumption imposes the restriction that the interferences among subsidized and controls are relevant only inside the LMAs and not significant outside.
The interferences are introduced in our empirical framework through an additional dummy variable (LMA), which represent Perugia and Terni LMA, and the interaction term with treatment and temporal variables. This framework allows to estimate two specific causal effects:

Average Treatment Effect using the Influenced Controls (ATEIC):

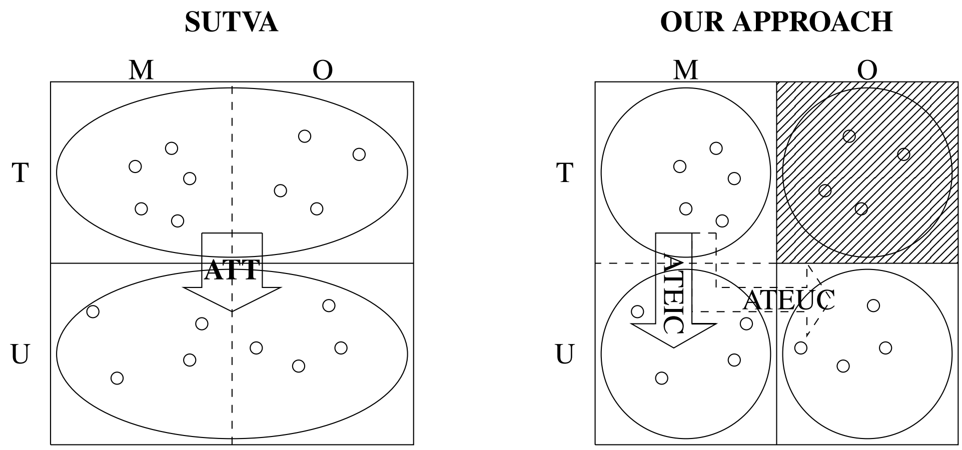
$$\begin{aligned} ATEIC = & E[y_i|D_i = 1, t_i = 1, LMA = 1] - E[y_i|D_i = 1, t_i = 0, LMA = 1] - \\ & E[y_i|D_i = 0, t_i = 1, LMA = 1] - E[y_i|D_i = 0, t_i = 0, LMA = 1] \end{aligned} \tag{2.3}$$

Average Treatment Effect using the Uninfluenced Control (ATEUC):

$$\begin{aligned} ATEUC = & E[y_i|D_i = 1, t_i = 1, LMA = 1] - E[y_i|D_i = 1, t_i = 0, LMA = 1] - \\ & E[y_i|D_i = 0, t_i = 1, LMA = 0] - E[y_i|D_i = 0, t_i = 0, LMA = 0] \end{aligned} \tag{2.4}$$

The ATEIC and the ATEUC allow diversified impacts, depending on the choice of the controls. The ATEUC represents the impact of the subsidies, taking into account the interferences; the ATEIC is a measure of the error in the estimation of the effects when we wrongly assume the validity of the SUTVA. However, the difference between ATEUC and ATEIC provides a measure of the spillover effects in response of the subsidies.
The presence of interferences is modelled comparing the outcome of only the treated units located in Perugia and Terni and the control groups on the basis of their inclusion or not in the influence area of the subsidized ones. In this way, we are able to estimate the influences of geographical localization and market concentration on treatment effects. An immediate comparison between standard and ”novel” approaches is provided by the following figure.

[10] Rosenbaum (2012) remarks how the interference can be expressed as 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 economic distance. Nevertheless, we focus only on the geographical dimension of the interferences between units, many are the studies that consider alternative measures of proximity on the identification of causal effects. Brock and Durlauf (2007), Cerulli (2015) and Arduini et al. (2014) focus on social interferences, meanwhile Arpino and Mattei (2013) model interferences as a function of firms size and geographical distances.



Left panel represents the standard approach when SUTVA is satisfied. The estimates of the ATT is implemented by comparing all the treated (T) with the untreated (U). Right panel shows our novel approach. We select only the subsidized units belonging to the main LMAs (M), excluding the other subsidized. The ATEIC requires the comparison with the controls located in M (influenced sample), while the ATEUC selects only the unsubsidised of the other (O) LMAs (uninfluenced).

2.3 Results

In this section we provide evidence on the effectiveness of public policies on the firms in Umbria, taking into account the presence of technological spillovers due to the conjunct action of regional policies and market concentration. This operation requires the empirical evaluation of the three distinct treatment effects (ATT, ATEIC, ATEUC) presented in the previous section. In Table 2.5 we show the results of our estimates in term of technological, economic and financial performances.

The estimates demonstrate the presence of additional effects for innovation and technological processes, but scarce results on economic and financial performances. First, we assume the validity of the SUTVA (column ATE in 2.5). The results indicate a major propensity to R&D process for the treated, both for internal and external research. The higher propensity on innovation is confirmed by the positive and significant impact on patents, innovation of product and production process, the development of better logistic systems and the acquisition of machinery, equipment and software devoted to the innovation process.
In addition, treated firms prefer to operate in international markets, in contra-position of a regional tendency of the controls. The international openness of the subsidized firms highlights the improvement of their relative competitiveness in regional market, making it more dynamic and global. Instead, the limited impact on firms performance is in line with

Table 2.5. Results

Input Variables at innovation and R&D						
	ATE		ATEIC		ATEUC	
Graduates (%)	0,57		1,35		-3,19	
Mkt Reg (%)	-16,98	***	-12,55		-17,10	*
Mkt Nat (%)	5,88		1,47		6,77	
Mkt EU (%)	2,38		3,45		5,69	
Mkt Non-EU (%)	9,36	***	8,86	***	7,09	*
Employes R&D	1,43		3,48		0,05	
Graduates R&D (%)	-4,54		-21,36		-7,97	
R&D intramuros (%)	36,56	***	46,62	***	31,29	***
R&D extramuros (%)	45,68	***	48,65	***	54,87	***
Total current expenditure	72,81		124,08		46,41	
Expenditure R&D personnel	54,73		102,92		-10,40	
Total expenses extramuros	9,12		-18,49		24,87	*
Total research expenditures	-117,70		136,85		-311,81	
Output Variables at innovation and R&D						
	ATE		ATEIC		ATEUC	
Product (%)	26,31	***	29,87	***	24,07	***
Service (%)	2,59		9,58		-3,70	
Production Process (%)	22,47	***	30,68	***	17,18	
Logistic System (%)	16,16	**	14,44		25,42	*
Machine,equipment,software(%)	20,69	***	21,82	**	13,35	
Patent (%)	25,66	***	25,85	**	28,36	**
Protection design and model(%)	8,28		9,82		13,26	
Brand (%)	5,66		7,30		6,16	
Copyright (%)	3,42		5,66		5,66	
Performance Variables						
	ATE		ATEIC		ATEUC	
Δ Equity	375580		584633		87697	
Δ Net assets	280712		499887		-347362	
Δ Net income	20274		-66884		176344	
Δ Output Value	-1660703		-3036829		-1033338	
Δ Personnel Costs	-119255		-118806		-523622	***
Δ Financial charges	27407		30119		9083	
Δ Extraordinary charges	-21266		1810		-91685	
Δ Amortization	215765	***	287742	**	188119	
Δ Fiscal charges	-4982		-45173		58276	
Δ Capital assets	32158		844060		-954457	
Δ Current assets	299079		-109014		1192512	
Δ Added Value	117942		88808		-183487	
Δ Ebitda	237197		207614		340135	*
Δ Ebit	81873		-3083		155234	
Δ ROI	0,34		-0,98		-1,27	

Legend: *** 99 % Significativity, ** 95 % Significativity, * 90 % Significativity other regional policy evaluation studies, such as Bronzini and Piselli (2016) and Corsino et al. (2012). The effects in terms of ATEUC (i.e. when the SUTVA is not valid) are similar in size and statistical significance.

The comparison between the ATEIC and ATEUC allows to identify technological spillovers due to regional policies and market concentration. This operation evidences some interesting differences on technological processes between influenced and uninfluenced units[11].

The results shows that firm concentration plays a determinant role in the choice between internal and external research; the influenced firms prefer to develop external research (both in term of extramuros research and expenses), while uninfluenced units tend to develop internal research. The last consideration is confirmed by higher expenses on R&D personnel for the uninfluenced, even if not statistical significant.

A second insight in comparing ATEIC and ATEUC regards the more intense effects on the influenced firms, in particular for the production process and product innovation. Interestingly, considering the development of logistic systems, we can observe a positive and significant effects limited to uninfluenced controls.

The third consideration regards the presence of a negative and significant effects on personnel costs for the controls located outside the influence areas of the treated. Recombining the results of the estimates in a unique framework, we can identify some interesting characteristics on the dissimilarities on the technological process between firms located inside and outside the influence area of the treated.

Summarising, the influenced controls tend to externalize their research activity, with a reduction on the number of employees to R&D and an increment of the extramuros expenses. The lack of internal activity is reflected in a lower propensity to product and process innovation and the improvement in their logistic systems in order to follow the entire technological process.

The uninfluenced, taking into account also the less concentrated market in which they operate, produce internal R&D and develop independently their innovative products. This is reflected in a number of firms that invest in production processes and technological raw materials higher in comparison with the influenced ones. Additional proof is constituted by the larger R&D personnel expenses, symptomatic of an higher requirement of qualified and expensive human capital.

In conclusion, we can gather that the influenced tend to create and develop some forms of research network in order to take advantage of the spillover effects due to market concentration and the proximity with the treated firms.

[11]Remark that the differences between this two samples depend on the geographical localization of the units. With the term *"influenced"* we indicate the unsubsidized located in Perugia and Terni LMAs, meanwhile the *"uninfluenced"* are the controls in the other LMAs.

Additional results

The results presented in the previous section highlight the presence of some technological spillovers. However, the peculiarities of regional productive structure requires an in-depth analysis. RUICS (2009) indicates the lack of large firms as one of the main structural problem in the region, highlighting a reduced average size of the regional enterprises. Additional estimates limited only to small firms sample are therefore useful.

Table 2.6. Additional Results

	Small Firms		**Manufacturing**	
Input Variables at innovation and R&D				
	ATEIC	ATEUC	ATEIC	ATEUC
Graduates (%)	-0,47	-7,43	10,67	4,78
Mkt Reg (%)	-14,72 *	-22,18 **	-1,25	1,38
Mkt Nat (%)	3,68	11,77	-2,95	0,55
Mkt EU (%)	4,70	5,31	-3,31	-3,03
Mkt Non-EU (%)	8,03 **	6,31 *	9,51 *	6,05
Employees R&D	6,07	4,32	-0,21	-4,53
Graduates R&D (%)	-16,48	-5,84	-23,48	0,38
R&D intramuros (%)	53,38 ***	35,33 ***	39,00 ***	20,82 *
R&D extramuros (%)	54,73 ***	59,51 ***	34,60 **	52,79 ***
Total current expenditure	-46,87	98,47 **	163,34	39,02
Expenditure R&D personnel	-30,41	59,55 **	124,67	-22,75
Total expenses extramuros	-20,89	50,11 *	25,42	20,15
Total research expenditures	-49,97	119,54 **	189,00	-385,54
Output Variables at innovation and R&D				
	ATEIC	ATEUC	ATEIC	ATEUC
Product (%)	32,37 ***	33,48 ***	14,37	5,28
Service (%)	-2,17	-8,42	15,84	11,29
Production Process (%)	30,00 **	18,89 **	43,64 ***	16,36
Logistic System (%)	20,00	26,94 *	27,88 *	36,97 **
Machine,equipment,software(%)	20,29 *	18,21 *	35,78 ***	8,50
Patent (%)	26,81 **	30,98 **	20,53	29,62 *
Protection design and model(%)	8,45	13,32	7,04	7,04
Brand (%)	4,44	6,53	-3,03	-12,12
Copyright (%)	6,67	6,67	6,67	6,67
Performance Variables				
	ATEIC	ATEUC	ATEIC	ATEUC
Δ Equity	20325	106560	1362941	140474
Δ Net assets	467031 *	-30603	290191	-395782
Δ Net income	34873	-82839	-429942	333369
Δ Output Value	-101256	-366314	1757665	-1193062
Δ Personnel Costs	-78578	-53972	95516	-703631 **
Δ Financial charges	-16428	31950	109224	-17425
Δ Extraordinary charges	-37108 *	-24638	118571	-102272
Δ Amortization	70674 *	88316 **	387028 *	204118
Δ Fiscal charges	-18648	3462	-119560	91971
Δ Capital assets	526037	533155	1663113	-1678038 *
Δ Current assets	-1068861	563622	3214236 *	-34167
Δ Added Value	-45215	-37722	160838	-193869
Δ Ebitda	33363	16250	65322	509762 *
Δ Ebit	-37431	-132708	-108669	332410
Δ ROI	-0,93	-1,60	-2,32	-1,24

Legend: *** 99 % Significativity, ** 95 % Significativity, * 90 % Significativity
With the term "Small firms" we consider only the enterprises with a number of employees between 10 and 49. The definition of manufacturing sector follows the ATECO 2007 classification (Nace rev.2)

Small firms estimates highlight an higher additional impact of the regional policies, confirming the empirical founding of the previous literature (see Bronzini and Piselli (2016) inter alia). Interesting results are found in terms of a lower openness to national and international

markets of the controls and a strong additionality on the number of treated that develop both internal and external research.
The effects on economic variables are still limited, even though a positive and significant impact on net assets. In addition the results provide evidence in favour of the development of spillover effects. The most significant effect is related to the expenditure component on the innovation processes. The wide ATEUC reflects the fact that small firms located outside the main LMAs invest less than the influenced controls, having similar results on innovation product. The estimates suggest the preference for the uninfluenced to develop internal research, confirmed also by coherent results on the production process and logistic systems in comparison with the ATEIC.
The results are heterogeneous by sectors. We estimate the effects in the sub-sample of the manufacturing[12]. The different research structure between influenced and uninfluenced controls is more clear in this sector. Instead, the evidence on the additionality of public policies on technological process are weak, even if the treated have a positive and significant effects on production process, logistic systems and the acquisition of machinery.
The impact on the influenced controls has a greater intensity. Some limited spillover effects are found for the Ebitda. In addition the personnel costs present a negative and significant ATEUC; results consistent with the one referred to the employees on R&D. The estimates on the manufacturing highlight how the uninfluenced controls present, on the whole, better technological and financial performances in comparison with the influenced untreated. This consideration suggests how being located in a more concentrated market produces negative externalities on the performances of the controls in the manufacturing sector.

2.4 Robustness check

A correct implementation of the DID approach requires that the data satisfy the ”common” trend assumption; i.e. the trend in the outcome variable for both treatment and control groups during the pre-treatment period are similar. Thus, in absence of treatment, there would not be differences in behaviour between the two groups and the deviation on temporal trend after the treatment identifies the treatment effects.
This assumption plays a fundamental role in the implementation of the Difference in Difference estimators. On one hand, it ensures unbiased estimates. Conversely, usually its validity is difficult to test and it assumed to be true a-priori. In this chapter we check the validity hypothesizing that the growth rate for the outcome of treated and controls follows

[12]The definition of manufacturing are based on the Italian classification of the economic activity (ATECO 2007). ATECO 2007 recalls the European definition and guidelines indicated in the NACE rev.2; in this way the data are comparable both at EU and extra-EU level. In detail, Manufacturing corresponds to the entire Section C of the classifications.

parallel paths during the pre-treatment period. In this way we are able to estimate the possible presence of different temporal trend between the groups.
This test consists in the implementation of the standard and novel DID approach in the pre-treatment period, checking for the presence of significant results. Common trend assumption is satisfied if there are not significant differences in pre-treatment trends.

Table 2.7. Robustness Check

	ATE	ATEIC	ATEUC
g Equity	0,30	0,05	-0,01
g Net assets	0,05	0,06	13,67
g Net income	-17,78	-41,81	-45,22
g Output Value	1,07	0,18	0,36
g Personnel Costs	6,81	13,67	13,61
g Financial charges	0,82	0,49	0,45
g Extraordinary charges	93,73	8,88	-70,13
g Amortization	-30,76	0,10	-12,04
g Fiscal charges	0,17	0,72	-0,31
g Capital assets	0,14	0,19	0,15
g Current assets	-0,07	-0,05	-0,07
g Added Value	4,67	8,13	12,01
g Ebitda	18,95	6,88	6,95
g Ebit	16,82	35,95	36,46
g ROI	3,63	7,63	6,59

*** 99 % Significativity, ** 95 % Significativity, * 90 % Significativity.

Legend: The reported statistics are expressed in terms of growth rate between 2004 and 2005. The estimates demonstrate the absence of significant differences in time trend before the treatment.

Table 2.7 shows the lack of meaningful differences in the economic performances for all the outcome variables used in the estimation of the ATT, ATEIC and the ATEUC during pre-treatment period. This results confirm the validity of the ”common trend” assumption.

2.5 Conclusions

Modern economic theory places a strong emphasis on the role of innovation and technical change in generating growth. In this paper we provide evidence on the effectiveness of the regional ”Competitiveness Package” in Umbria. Starting from a ”traditional” approach, we introduce the possibility of interactions between firms, on the basis of their geographical localization and market concentration. Our approach allows to differentiate the effects in consideration of territorial strength, in order to identify the presence of technological spillovers.

The results provide evidence in favour of the effectiveness of regional policies. The subsidized firms have additional and significant effects in the improvement of their technological capabilities, both in terms of input and output of the R&D processes; while there are no impacts on firms performances. The lack of short-term effects on the economic and financial accounts can be explained, at least partially, by regional policies.
In fact, their main objective is to foster research and innovation of the firms. This produces a change in firms behaviour which stimulate technological production and R&D process. In this way, seems reasonable to expect a long temporal lag between the production of the innovation and economic and financial benefits on the activities of the firms. However, the analysis of the effects on medium and long period of the incentives requires the availability of data referred to broader time window. This will be an interesting extension for further research.
In addition, the impact is heterogeneous across firms. The estimates highlight the relevance of geographical concentration, not only with beneficial effect on the innovative variables. In fact we have found some empirical evidence on the different structure of the process of innovation. Firms that are not treated but influenced by the policy tend to prefer external research, increasing their link with the other territorial components.
Instead, the uninfluenced ones prefer to develop internal research. This is evidenced by a major requirement of specialized employees, with detrimental effects on personnel costs. These results show how the localization in the influence area of the treated favour the diffusion of technological spillovers. In detail, the novel approach proposed in this chapter permits to identify the development of spillover effects through the comparison between ATEIC and ATEUC. We find evidence of spillovers in terms of total expenses extramuros, number of patents, development of logistic systems and the Ebitda.
The effectiveness of public policies is not only influenced by geographical location. As expected, also firms size is important. Small firms present a bigger additional impact, both in terms of policy effectiveness and for the technological spillovers. The most evident results are found considering the development of spillover effects for R&D expenditures. Indeed, the uninfluenced controls tend to spend less for technological input variables, both for personnel and research costs.
Furthermore, the estimates referred to the manufacturing show the presence of different technological paths compared with the previous cases. In fact, the limited effects on the innovation of product are counterbalanced by the significant impact on the development of new production process and on the acquisition of machinery and equipment. Besides, it is important to remark the development of negative externalities on the influenced controls. This shows how process innovation, in this sector, is affected by market concentration and does not necessarily imply the development of research network.
In addition, a well-informed public administration can be considered as a key issues for the

redefinition of public policies. The analysis of the questionnaires proposed by the Umbria Region to the firms provide us some insights into the strengths and weaknesses of the instruments from the entrepreneurs viewpoint.

Table 2.8. Degree of satisfaction of the firms

Satisfaction's degree of enterprises	
Weakness	Strengths
Approval times Dispensing times Certainty obtaining incentive Simplicity of the procedure	Allocation Procedure Mode / entity of the incentive Knowledge of procedure by P.A. Quality relationship with P.A.

Source: Our elaboration of the questionnaires.

Legend: This table resumes the degree of satisfaction of the enterprises on the procedure behind the administration of public policies and, in general, on the behaviour of the Public Administration

Table 2.8 shows how the entrepreneurs are particularly satisfied with the behaviours of the public administration, but require shorter approval times and a major simplicity of the procedure. In conclusion the results seem to confirm empirically a strict local linkage and the presence of significant local technological spillovers as a response of the conjunct influence of the regional policies and the geographical concentration.
This concept constitutes the ”core” of smart specialization policies in Europe and our novel approach can be considered a powerful tool in order to provide evidence on the presence and development of technological spillovers.

Chapter 3

Policy Evaluation in presence of interferences: a spatial hierarchical DID approach[1]

The mainstream approach in policy evaluation focuses on the assessment of public policies effectiveness ruling out the presence of interferences and, consequently, the occurrence of spillovers effects. This is quite surprising, since the main scope of policy intervention is to stimulate positive spillovers among agents. A typical case is the public support to R&D. In this context, policies aim to stimulate a wider and faster diffusion of knowledge spillovers. Knowledge spillovers have a twofold relevance in regional sciences perspective.
On one hand, the spatial extent of knowledge spillovers constitutes an important factor in modelling regional conditions for innovation and R&D. Part of the literature remarks the relevance of geographical space on the diffusion of knowledge spillovers by the formation of cooperative relationship between regional actors[2].
On the other hand, policies enhancing knowledge spillovers favour the formation of relationships between units through, for example, incentives devoted to the formation of stable network of firms. These policies reveal the development of an additional channel to the process of formation and dissemination of knowledge spillovers.
The estimation of the differentiated channels to facilitate the formation of knowledge spillovers is a great challenge for policy evaluator, inasmuch it requires to distinguish between total and indirect effects in response to the treatment. However, the traditional

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[2]Regional scientists introduces concepts like industrial districts (Porter, 1998), innovation network (Camagni, 1991) and regional innovation systems (Fritsch and Slavtchev, 2011) to analyse the connection between geographical proximity and cooperative behaviours in the development of knowledge spillovers.

approach in policy evaluation does not allow to evaluate the additional indirect effect. Actually, the aim of the policy maker is not limited to the development of knowledge spillovers, but, in wider terms, to to enhance innovation and growth by stimulating direct and indirect effects.

Hudgens and Halloran (2012) propose a definition of direct and indirect effects. The first is the response of the individuals to a treatment, while the latter represents the response to the interferences between units. The knowledge of the indirect impact of the policies is crucial to ensure unbiased estimation of treatment effects. Moreover, it played a fundamental role in the case in which treatment induces interactions.

Rosenbaum (2012) argues that interferences may be "unlimited in extent and impossible to specify in form", making the problem of the specification of the interactions difficult to solve. However, it is possible to consider interferences by a function of proximity between units. Appropriate measure of proximity are the geographical distance, the nodal distance in a known social network or metrics of socio-economic distance.

Research on drawing inference on causal effects in presence of interferences is not yet common, although some exceptions exist (Verbitsky and Raudenbush, 2004; Sobel, 2006; Rosenbaum, 2012; Tchetgen and VanderWeele, 2010; Hudgens and Halloran, 2012; Kao and Toulis, 2013; Sinclair et al., 2012; De Castris and Pellegrini, 2015; Cerulli, 2015). However most of the existing works are theoretical and/or focalized on randomized experiments. Applications in the context of observational studies which address SUTVA violations are still rare.

Cerqua and Pellegrini (2014) and Di Gennaro and Pellegrini (2016a) propose two different approaches to isolate the presence of spillovers. The first considers the untreated until a certain cut-off distance as affected and evaluate the presence of spillovers through a CEM-matching between the affected and the other controls. The latter identifies the occurrence of spillover effects by a comparison between treated and controls on the basis of the market concentration in which they operate[3].

Verbitsky-Savitz and Raudenbush (2012), analysing the causal effect of Chicago's community policing program (a community-wide intervention) on neighbourhoods' crime rates, model the potential outcomes in any local area as a function of the treatment assignments of all the other units within the framework of a generalized linear model with spatially auto-correlated random effects.

Sobel (2006), estimating the treatment effect of the Moving To Opportunity (MTO) program, shows the possible consequences of a violation in the SUTVA by the definition of different causal "estimands" of interest. The aforementioned author, allowing for the presence of interferences between participants, estimates a non-zero impact on the potential outcome of the untreated (no impact in the case in which the SUTVA still holds).

[3]This method is presented in Chapter 2.

Arpino and Mattei (2013), considering interactions between units but assuming the validity of the SUTVA between different groups (in their case sector of activity), propose a measure of proximity based on a function of firms' characteristic, like geographical distance between firms and firms' size.
To resume, the feature that links these works is the evaluation of the presence of indirect effects through the comparison of appropriate treated and control groups. In this way it is possible to approximate the presence of interferences between units with a predetermined measure of proximity and, relaxing SUTVA hypothesis, identify the impact of the interactions on causal effect.
A different approach is proposed in the works of Manski. Manski (1993) explains how the impossibility to distinguish between endogenous and contextual interactions and the presence of correlated effects reveals the so-called "Reflection Problem". The above mentioned author refers to endogenous effect as the contemporaneous and reciprocal influences of peers, whereas contextual effect includes measures of peers unaffected by current behaviour. The identification problem arises because mean conduct in the group is itself determined by the behaviours of group members, i.e. data on outcomes do not allow to discriminate if group behaviour actually affects individuals conducts or it is simply the aggregation of individual behaviours.
Manski (1993), Brock and Durlauf (2001) and Moffitt (2001) propose alternatives to the linear-in-mean model to suggest possible solutions to the identification problem. The set of alternatives aims to separate peer influences in endogenous and contextual effects and includes variation in individual behaviour over the time (lagged vs contemporaneous), non linear function or the inclusion of the group median behaviour as alternative to the mean. Further developments on this approach include the identification of binary choice model with social interaction (Brock and Durlauf, 2007), restrictions on the shape of the response function (Manski, 2013)[4] and estimation of structural interaction effects in a social economics context by a spatial autoregressive model (Lee, 2006).
Gibbons and Overman (2012) demonstrate that spatial econometrics techniques can solve the identification problem. Sinclair et al. (2012) suggest a third method to address the violation of the no-interference assumption. In detail, they design a multi-level experiment in which treatments are randomly assigned to individuals and, varying proportions of the neighbours, they find evidence of within-household spillovers (no evidence of spillovers across households).
The aforementioned authors suggest that multi-level experiment can be extended to a wide branch of application, including what they define as "policy diffusion" (research and development, environmental policies, etc.) and in general to any circumstances in which the intervention occurred in one location influences the outcome in nearby areas.

[4]Manski introduces the concept of Constant Treatment Response (CTR) and Semi-Monotone Treatment Response (SMTR) as alternatives to SUTVA hypothesis.

Corrado and Fingleton (2012), analysing a spatial autocorrelated model, isolate indirect effects by differentiating the model for the mean at neighbourhood level[5]. Literature analysis shows that the growing interest on empirical research in presence of interactions has not yet led to the development of a unique theoretical and methodological framework. This chapter aims to address identification problem in presence of interferences by proposing a novel approach that allows to recombine direct and indirect effects in the ATE.

3.1 Potential Outcome Model with interferences

The idea behind the definition of a novel framework relies on the "traditional" Potential Outcome Model. Notwithstanding, in our novel framework interferences are not considered as a nuisance term, assuming a fundamental role in the identification of the causal effects.

$$y_i = D_i y^1 + (1 - D_i) y^0 = \begin{cases} y^1 & \text{if } D = 1 \\ y^0 & \text{if } D = 0 \end{cases} \tag{3.1}$$

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, making intractable their identification. However, to impose a restriction on the extension of the interferences allows to overcome the identification problem. 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. We start from a different version of the POM (eq. 3.2) which corresponds to the "traditional" potential outcome to whom we add and subtract the equation in 3.1 multiplied by D_j. This term, derived applying a spatial lag of the treatment variable, represents neighbours' state of treatment:

$$y = Dy^1 + (1 - D)y^0 + D_j(Dy^1 + (1 - D)y^0) - D_j(Dy^1 + (1 - D)y^0) \tag{3.2}$$

3.2 can be rearranged and write as:

$$y = \underbrace{(1 - D_j)(Dy^1 + (1 - D)y^0)}_{\text{Effect without interactions}} + \underbrace{D_j(Dy^1 + (1 - D)y^0)}_{\text{Effect of the interactions}} \tag{3.3}$$

[5]Gibbons et al. (2014) propose an alternative approach for identifying causal parameters in presence of interactions within clusters, based on a process of spatial differencing.

Equation 3.3 permits to distinguish between direct and indirect effects. In detail, the first term in 3.3 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[6]. In this way, we can decompose the ATE as the sum of direct and indirect effects, as reported in 3.4.

$$ATE = ADTE + AITE = (1 - D_j)ATE + D_j ATE \tag{3.4}$$

This idea constitutes the focal point of the Difference-in-Differences approach followed in the remainder of the chapter.

3.2 Introducing the Interferences in DID approach

The "traditional" DID model allows to evaluate the ATE as the parameter β_3 of the following equation:

$$Y = \beta_0 + \beta_1 D + \beta_2 T + \beta_3 DT \tag{3.5}$$

or expressed in terms of expectations as in 3.6:

$$\begin{aligned} a_S &= E[Y|D = 1, T = 1] = \beta_0 + \beta_1 + \beta_2 + \beta_3 \\ b_S &= E[Y|D = 1, T = 0] = \beta_0 + \beta_1 \\ c_S &= E[Y|D = 0, T = 1] = \beta_0 + \beta_2 \\ d_S &= E[Y|D = 0, T = 0] = \beta_0 \\ ATE &= (a_S - b_S) - (c_S - d_S) = \beta_3 \end{aligned} \tag{3.6}$$

The formulations in 3.5 and 3.6 provide correct estimates of the treatment effect, even if it exclude the presence of inferences between units. To include this hypothesis a substantial review of the Diff-in-Diffs approach is required. The objective of this paper is to adapt the intuition in 3.2 in the regression model expressed in 3.5.
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 3.7:

$$Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j D + \beta_6 D_j Dt \tag{3.7}$$

Using the specification in 3.7 we are able to estimate simultaneously both total, direct and

[6]Different typologies of neighbours can be considering on the basis of the adopted spatial framework.

indirect causal effects. Applying the "standard" Diff-in-Diffs approach to 3.7 provides unbiased estimates of the ATE, even if, in this case, we are able to decompose the ATE to identify and isolate the quota of impact attributable to the interferences. In this way the formulation of the ATE becomes:

$$ATE = \beta_3 + \beta_4(\overline{D_j^1} - \overline{D_j^0}) + \beta_6 \overline{D_j^1} \tag{3.8}$$

The term $\overline{D_j^1}$ (resp. $\overline{D_j^0}$) indicates the average share of treated neighbours for subsidized (resp. control) units. As already said, the ATE in 3.8 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 3.7 we derive the impact of direct and indirect causal effects:

$$\begin{aligned}
a &= E[Y|D=1, t=1, D_j \neq 0] = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 \overline{D_j^1} + \beta_5 \overline{D_j^1} + \beta_6 \overline{D_j^1} \\
b &= E[Y|D=1, t=1, D_j = 0] = \beta_0 + \beta_1 + \beta_2 + \beta_3 \\
c &= E[Y|D=1, t=0, D_j \neq 0] = \beta_0 + \beta_1 + \beta_5 \overline{D_j^1} \\
d &= E[Y|D=1, t=0, D_j = 0] = \beta_0 + \beta_1 \\
e &= E[Y|D=0, t=1, D_j \neq 0] = \beta_0 + \beta_2 + \beta_4 \overline{D_j^0} \\
f &= E[Y|D=0, t=1, D_j = 0] = \beta_0 + \beta_2 \\
g &= E[Y|D=0, t=0, D_j \neq 0] = \beta_0 \\
h &= E[Y|D=0, t=0, D_j = 0] = \beta_0
\end{aligned} \tag{3.9}$$

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 3.10:

$$ADTE = b - d - f + h = \beta_3 \tag{3.10}$$

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.

$$AITET = a - c - b + d = \beta_4 \overline{D_j^1} + \beta_6 \overline{D_j^1} \tag{3.11}$$

$$AITENT = e - g - f + h = \beta_4 \overline{D_j^0} \tag{3.12}$$

3.11 and 3.12 represent respectively the AITET (Average Indirect Treatment Effects on the

Treated) and the AITENT (Average Indirect Treatment Effects on the Controls) [7]. In this chapter we analyse the correctness of the intuition behind the DID model with interferences. In the next section we present the results of our simulations.

3.3 Montecarlo Simulation

The novel approach developed in this chapter allows to overcome the identification problems related to the inclusion of interferences between units in causal analysis. Notwithstanding, the aim of this paragraph is to determine an appropriate estimation procedure able to provide unbiased and efficient estimates of the causal effects. For these reasons, two different Montecarlo Simulations were required. This procedure takes into account the behaviour of the causal effects when we increase both the number of replications (100 and 250) and the sample size (225, 400 and 625 units). To address the identification problems in presence of interferences we propose a two-stage analysis.

In the first stage, we open up to the possibility of spatial interactions under the assumption of uniform spatial distribution of the units (i.e. firms are located in a regular grid). In this step of our analysis we compare the performances of both a linear estimator and a spatial error model.

In the second stage we consider a spatial agglomerated distribution of the units. Moreover, we take into account possible differences between areas through the inclusion of a random neighbourhood effect. This stratified approach makes possible the introduction of an alternative hierarchical model. Under this framework we are able to simulate a ”real” world case which allows to take into account the existence of both clustered and undeveloped areas. In this stage, we compare the results of a linear, a spatial and an additional spatial hierarchical procedure.

3.3.1 Spatial Heterogeneity

The first case introduces spatial heterogeneity on a uniform spatial distribution of the units. This assumption has a twofold impact on our analysis. On one hand, imposing the restriction on the distribution of the units allows to consider the impact of spatial interferences on causal effects. On the other hand, the presence of spatial heterogeneity enables the inclusion of a spatial error model. In this stage of our analysis we evaluate the unbiasedness of the DID model with interferences by a comparison between a linear (DID) and a spatial (Spat-DID) approach[8].

[7] The proofs of total, direct and indirect treatment effects are in Appendix A.

[8] It is noteworthy to recall that Gibbons and Overman (2012) demonstrate that spatial econometrics allows to address identification problem in presence of interferences.

Furthermore, the inclusion of spatial heterogeneity in the analysis ensure the unbiasedness of both linear and spatial models[9]. Under these hypothesis, we simulate the following DGP:

$$\begin{cases} y_i = \alpha + \beta X + u_i \\ u_i = \lambda W u_i + \epsilon_i \\ \beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6) = (1, 1, 1, 0.1, 0.1, 0.1) \\ X = (D, t, Dt, D_j t, D_j D, D_j Dt) \\ \lambda = 0.5 \\ D_j = WD \text{ with W first order queen contiguity matrix} \\ D_j = d \in [0, 1] \\ \epsilon_i \sim N(0, 1) \end{cases}$$

where the vector X represents the covariates of the DID model in presence of interferences, the error term u_i presents spatial autocorrelation depending on the value of the parameter λ, D_j indicates the state of treatment of the neighbours units and it can assume values between 0 and 1 (i.e. W is a row-standardized spatial matrix). More in detail, the value of D_j for unit i is obtained as:

$$_iD_j = WD_i = \begin{cases} d \in (0, 1] & \text{when } \sum_{i=1}^{n} w_i D_i = d \\ 0 & \text{when } \sum_{i=1}^{n} w_i D_i = 0 \end{cases}$$

This case includes the presence of spatial correlated treatment variable obtained by the following spatial decay function: $h(x) = e^{-\phi * distance}$, with $\phi = 1.25$. Therefore, the above DGP produces a spatial distribution of the variables as reported in Figure 3.1.

Top-left panel shows the spatial distribution of the treatment variable on a regular lattice. Top-right panel exhibits the different level of interferences (i.e. quota of neighbours treated) for each units, while bottom-right (resp. left) panel illustrates the distribution of the response variable at time 0 (resp. 1).

The results of the simulation of the "traditional" DID model shows an upward bias in the estimation of the ATE. In other words, including the presence of interferences the ATE become a function of both direct and indirect effects. Consequently, the amplitude and sign of the bias in the ATE follows are in line with the sign and amplitude of direct and indirect causal effects. However, taking into account the interaction between units through the novel methodology we are able to produce an unbiased decomposition of the ATE in both its direct and indirect components [10].

[9]"*A spatial error model is a special case of a regression with a non-spherical error term, in which the off-diagonal elements of the covariance matrix express the structure of spatial dependence. Consequently, OLS remains unbiased, but it is no longer efficient and the classical estimators for standard errors will be biased*"(Anselin, 2007)

[10]See Appendix B.

Figure 3.1. Spatial Distribution with Spatial Heterogeneity

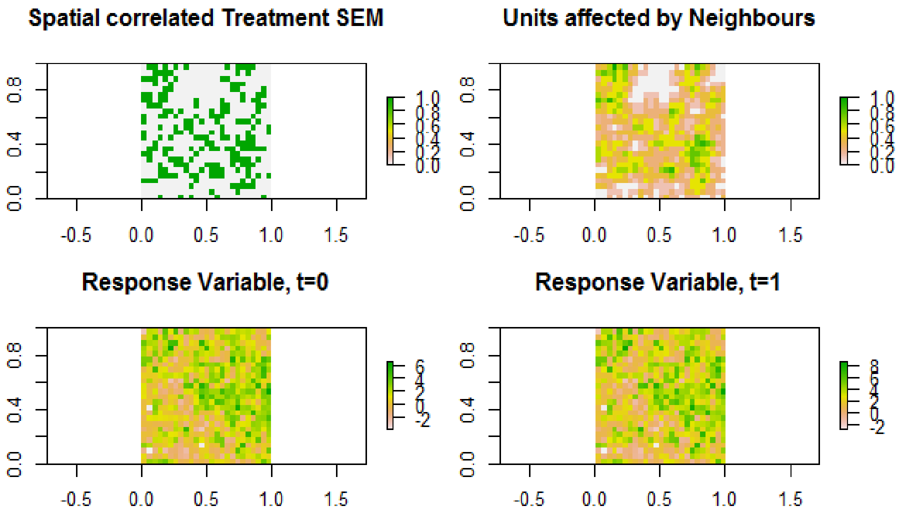


Table 3.1. Results of "Traditional" DID with spatial heterogeneity

			DID		Spat-DID		
	n	m	Result	S.Error	Result	S.Error	True
Cons	225	100	1.1021	0.1167	1.0497	1.2869	1
D			1.0412	0.2113	1.0288	0.0725	1
t			1.0266	0.1650	1.0402	1.8200	1
ATE			1.0525	0.2988	1.0126	0.1026	1
Cons	400		1.0672	0.0916	1.0936	1.1837	1
D			1.0708	0.1649	1.0321	0.0541	1
t			1.0266	0.1295	1.0398	1.6741	1
ATE			1.0536	0.2332	1.0128	0.0765	1
Cons	625		0.9298	0.0752	0.9190	1.0857	1
D			1.0586	0.1357	1.0305	0.0433	1
t			1.0267	0.1064	1.0409	1.5354	1
ATE			1.0532	0.1918	1.0128	0.0612	1
Cons	225	250	0.9798	0.1139	1.0072	1.1930	1
D			1.0279	0.2063	1.0334	0.0729	1
t			1.0266	0.1611	1.0395	1.6871	1
ATE			1.0524	0.2918	1.0123	0.1031	1
Cons	400		0.9142	0.0951	0.9468	1.2353	1
D			1.0396	0.1715	1.0257	0.0540	1
t			1.0267	0.1345	1.0410	1.7470	1
ATE			1.0535	0.2425	1.0126	0.0763	1
Cons	625		0.9262	0.0768	0.9243	1.0633	1
D			1.0261	0.1384	1.0299	0.0431	1
t			1.0268	0.1086	1.0397	1.5037	1
ATE			1.0533	0.1957	1.0129	0.0610	1

Legend: Table 3.1 presents the results of Montecarlo Simulation in presence of spatial heterogeneity. n represents the number of units (225, 400 and 625), m the number of replications (100 and 225), the columns DID (resp. Spat-DID) display the results of linear (resp. spatial) model, while the last column indicates the true value of the parameter.

Table 3.2. Bias/Efficiency DID with spatial heterogeneity

			BIAS		RMSE		DID-Estimate	
	n	m	OLS	Spat-DID	OLS	Spat-DID	OLS	Spat-DID
ATE	225	100	0.0525	0.0126	1.4514	0.4867	0.0000	0.0399
	400		0.0536	0.0128	1.5187	0.4835	0.0000	0.0408
	625		0.0532	0.0128	1.5622	0.4838	0.0000	0.0404
ATE	225	250	0.0524	0.0123	1.4169	0.4888	0.0000	0.0401
	400		0.0535	0.0126	1.5778	0.4827	0.0000	0.0409
	625		0.0533	0.0129	1.5946	0.4823	0.0000	0.0404

Legend: Table 3.2 indicates the bias of the ATE in presence of interferences. Columns BIAS indicates the differences between the estimated ATE and the expected value of β_3, columns RMSE represents the Root Mean Square Error, while the columns labeled as DID-Estimate shows the bias of the double differences compared to the estimate of the regression model.

Table 3.3. Results Novel DID with spatial heterogeneity

	n	m	DID Result	DID S.Error	Spat-DID Result	Spat-DID S.Error	True
Cons	225	100	1.1021	0.1154	1.0510	1.2894	1
D			1.0804	0.3896	1.0100	0.1258	1
t			0.9632	0.2267	1.0096	1.8279	1
Dt			1.0368	0.5734	0.9946	0.2050	1
Djt			0.2366	0.5910	0.0847	0.3286	0.1
DjD			-0.1109	0.8428	0.0644	0.3505	0.1
DjDt			-0.0366	1.3326	0.1043	0.5206	0.1
Cons	400		1.0672	0.0908	1.0909	1.1843	1
D			0.9845	0.3035	1.0035	0.0942	1
t			0.9881	0.1776	1.0042	1.6773	1
Dt			1.0119	0.4466	0.9972	0.1536	1
Djt			0.1507	0.4601	0.0895	0.2442	0.1
DjD			0.2028	0.6403	0.0941	0.2614	0.1
DjDt			0.0493	1.0165	0.1052	0.3887	0.1
Cons	625		0.9298	0.0749	0.9162	1.0860	1
D			0.9940	0.2485	0.9980	0.0753	1
t			0.9721	0.1477	1.0066	1.5376	1
Dt			1.0279	0.3663	0.9940	0.1226	1
Djt			0.2071	0.3852	0.0802	0.1977	0.1
DjD			0.1639	0.5242	0.1127	0.2101	0.1
DjDt			-0.0071	0.8359	0.1094	0.3119	0.1
Cons	225	250	0.9798	0.1127	1.0010	1.1921	1
D			1.0318	0.3778	0.9985	0.1263	1
t			1.0068	0.2217	0.9926	1.6902	1
Dt			0.9932	0.5564	1.0060	0.2062	1
Djt			0.0699	0.5770	0.1200	0.3295	0.1
DjD			-0.0235	0.8105	0.1213	0.3546	0.1
DjDt			0.1301	1.2855	0.0907	0.5279	0.1
Cons	400		0.9142	0.0944	0.9433	1.2383	1
D			1.0034	0.3148	0.9950	0.0938	1
t			0.9873	0.1853	0.9970	1.7536	1
Dt			1.0127	0.4636	1.0030	0.1526	1
Djt			0.1449	0.4800	0.1093	0.2444	0.1
DjD			0.0925	0.6644	0.1032	0.2603	0.1
DjDt			0.0551	1.0560	0.0946	0.3861	0.1
Cons	625		0.9262	0.0765	0.9199	1.0649	1
D			0.9885	0.2538	0.9996	0.0751	1
t			1.0301	0.1510	1.0010	1.5077	1
Dt			0.9699	0.3741	0.9994	0.1221	1
Djt			-0.0097	0.3934	0.0978	0.1974	0.1
DjD			0.0906	0.5340	0.1035	0.2090	0.1
DjDt			0.2097	0.8520	0.1002	0.3102	0.1

Legend: Table 3.3 presents the results of the novel DID model in presence of spatial heterogeneity. n represents the number of units (225, 400 and 625), m the number of replications (100 and 225), the columns DID (resp. Spat-DID) display the results of linear (resp. spatial) model, while the last column indicates the true value of the parameter.

Table 3.4. Bias Novel DID with spatial heterogeneity

	n	m	BIAS OLS	BIAS Spat-DID	RMSE OLS	RMSE Spat-DID
ATE	225	100	0.0368	-0.0054	1.4307	0.4846
AITET			0.0000	-0.0110	1.4307	0.4846
AITENT			0.1366	-0.0153	1.4307	0.4846
ATE	400		0.0119	-0.0028	1.5025	0.4820
AITET			0.0000	-0.0053	1.5025	0.4820
AITENT			0.0507	-0.0105	1.5025	0.4820
ATE	625		0.0279	-0.0060	1.5532	0.4828
AITET			0.0000	-0.0104	1.5532	0.4828
AITENT			0.1071	-0.0198	1.5532	0.4828
ATE	225	250	-0.0068	0.0060	1.3974	0.4865
AITET			0.0000	0.0107	1.3974	0.4865
AITENT			-0.0301	0.0200	1.3974	0.4865
ATE	400		0.0127	0.0030	1.5632	0.4813
AITET			0.0000	0.0038	1.5632	0.4813
AITENT			0.0449	0.0093	1.5632	0.4813
ATE	625		-0.0301	-0.0006	1.5857	0.4813
AITET			0.0000	-0.0021	1.5857	0.4813
AITENT			-0.1097	-0.0022	1.5857	0.4813

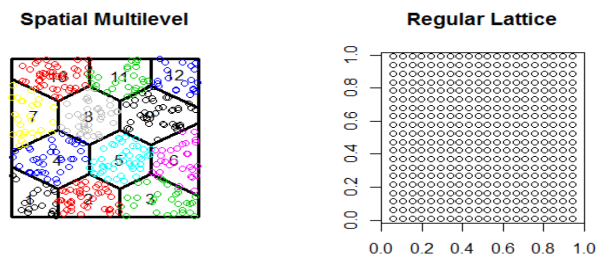
Legend: Table 3.4 indicates the bias of the ATE in presence of interferences. Columns BIAS indicates the differences between the estimated causal effects and their expected value, columns RMSE represents the Root Mean Square Error.

In Table 3.2 we demonstrate how the results of the double differences approach is coincident with the linear regression model (Column DID-Estimate), nevertheless the RMSE demonstrates that the spatial model suits better with the DGP. In Tables 3.3 and 3.4 we introduce the formulation of our novel Diff-in-Diff with interferences. The results for the linear model are biased, whereas spatial model reduces its bias when the sample size and the number of replications increase. Furthermore, both models do not produce significant effect. To conclude, the analysis of this case does not allow to identify a unique framework able to provide unbiased and efficient causal effects in presence of interferences. Specifically, linear model is able to estimate the true value of the ATE, while spatial model is preferable to distinguish between direct and indirect effects. The ambiguous and not satisfactory conclusions obtained in the analysis of this case has required the introduction of an alternative hierarchical method.

3.3.2 Spatial Heterogeneity with Neighbourhood Effects

The second case opens up to the possibility of spatial agglomeration between units. In this framework, we consider 2 different level of hierarchy. The first corresponds to the unit level, while the second indicates a macro-level in which the units are located (i.e. we can think to the spatial distribution of the firms within some territorial areas, like provinces, regions, etc.).

Figure 3.2. Difference in Spatial Distribution of units



Note: Figure 3.2 represents different spatial distribution of the units. Left panel shows the multilevel case: the different colours of the units indicates the location in one macro-level. Right Panel indicates a uniform spatial distribution of the units.

In Figure 3.2 we point out the differences between spatial agglomeration and uniform distribution of the units. In detail, in the so-called spatial multilevel approach we identify 12 distinct macro-areas. The location in one area is random, while we open up to the possibility of agglomeration inside the macro-areas. This hypothesis allows us to propose a two-level hierarchical model to estimate the DID with interferences.

$$Y = \beta_0 + \beta_1 D + \beta_2 t + \beta_3 Dt + \beta_4 D_j t + \beta_5 D_j D + \beta_6 D_j Dt + \epsilon_j + u_i, \quad \text{where}$$

$$\textbf{I Level: } Y = \beta_{0j} + \beta_{1j} D + \beta_{2j} t + \beta_{3j} Dt + u_i$$
$$\textbf{II Level: } \begin{cases} \beta_{0j} = \beta_0 + \epsilon_j \\ \beta_{1j} = \beta_1 + \beta_5 D_j \\ \beta_{2j} = \beta_2 + \beta_4 D_j \\ \beta_{3j} = \beta_3 + \beta_6 D_j \end{cases} \tag{3.13}$$

The estimation procedure in 3.13 is introduced in the columns indicated with SH-DID. The consideration of a hierarchical model has a twofold relevance. On one hand, Corrado and Fingleton (2012) observe how multilevel approach proposes alternative solutions to overcome the identification problem in presence of interferences. On the other hand, hierarchical model controls for the presence of heteroskedasticity both at unit and neighbourhood level with a substantial improvement of the quality of the estimates. Furthermore, the ambiguous results obtained in the previous case does not allows to identify a unique framework able to provide correct total, direct and indirect effects. For these reasons, we modify the DGP in 3.3.1 introducing the presence of random effects at neighbourhood level.

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

The major differences in the DGP consists in the different determination of the spatial weight matrix. While in 3.3.1 we use a row-standardized queen contiguity matrix at unit level, in this circumstance we restrict the interactions to the belonging or not in a macro-area. Two different units are considered neighbour only if they are located in the same macro-area. In other words, considering the presence of n_j units in a neighbourhood we attribute to each units in the macro-area the same weight $w_{ij} = \frac{1}{n_j - 1}$. Under this hypothesis, we are able to estimate only intra-clusters indirect effects.

Figure 3.3. Spatial Distribution with Neighbourhood Effects

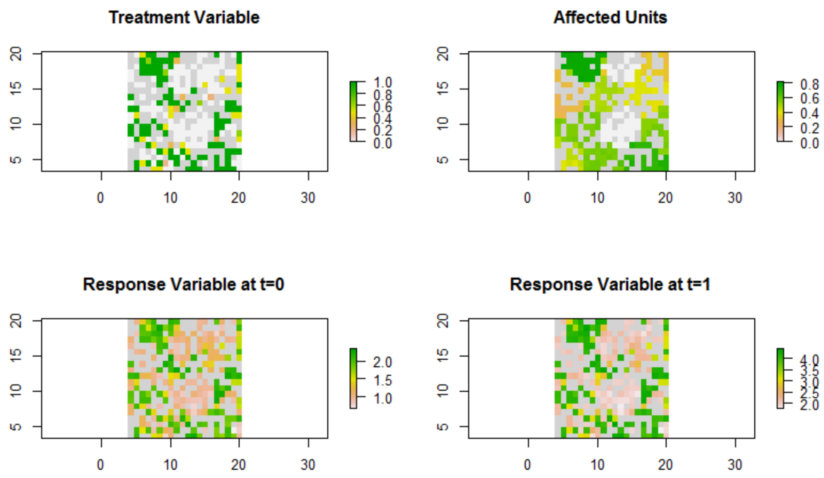


Figure 3.3 shows the graphical representation of this DGP[11]. In this case, the units presents an agglomerated distribution in the space. Consequently, the presence of areas in which there are not units is represented with grey cells. Moreover, the colour of every cell indicates the mean level of the units located in that precise point.

Table 3.5. Results of "Traditional" DID with neighbourhood effects

			DID		Spat-DID		SH-DID		
	n	m	Result	S.Error	Result	S.Error	Result	S.Error	True
Cons	225	100	0.9950	0.0136	0.9974	0.0556	1.0020	0.0525	1
D			1.0542	0.0209	1.0484	0.0081	1.0403	0.0079	1
t			1.0370	0.0192	1.0443	0.0787	1.0375	0.0071	1
ATE			1.0624	0.0296	1.0451	0.0115	1.0613	0.0107	1
Cons	400		1.0009	0.0073	0.9997	0.0286	1.0033	0.0272	1
D			1.0465	0.0111	1.0494	0.0063	1.0415	0.0061	1
t			1.0374	0.0103	1.0444	0.0404	1.0378	0.0055	1
ATE			1.0625	0.0157	1.0461	0.0089	1.0618	0.0083	1
Cons	625		1.0002	0.0046	1.0008	0.0139	1.0047	0.0134	1
D			1.0493	0.0069	1.0477	0.0053	1.0407	0.0052	1
t			1.0400	0.0065	1.0464	0.0197	1.0402	0.0048	1
ATE			1.0606	0.0097	1.0464	0.0076	1.0602	0.0071	1
Cons	225	250	0.9942	0.0132	0.9946	0.0531	0.9992	0.0500	1
D			1.0480	0.0203	1.0468	0.0084	1.0387	0.0081	1
t			1.0370	0.0187	1.0442	0.0751	1.0374	0.0072	1
ATE			1.0622	0.0287	1.0450	0.0118	1.0613	0.0110	1
Cons	400		1.0000	0.0074	0.9999	0.0289	1.0038	0.0275	1
D			1.0489	0.0114	1.0492	0.0066	1.0412	0.0064	1
t			1.0372	0.0105	1.0442	0.0409	1.0375	0.0057	1
ATE			1.0626	0.0161	1.0460	0.0093	1.0619	0.0087	1
Cons	625		0.9973	0.0045	0.9978	0.0133	1.0013	0.0129	1
D			1.0493	0.0067	1.0482	0.0053	1.0413	0.0052	1
t			1.0397	0.0063	1.0460	0.0188	1.0399	0.0048	1
ATE			1.0602	0.0095	1.0460	0.0076	1.0596	0.0071	1

Legend: Table 3.5 presents the results of Montecarlo Simulation in presence of neighbourhood effects. n represents the number of units (225, 400 and 625), m the number of replications (100 and 225), the columns DID,Spat-DID and SH-DID display, respectively, the results of linear, spatial and hierarchical models, while the last column indicates the true value of the parameter.

The presence of interferences produces biased estimates in the "traditional" DID for the 3 different procedures. However, linear model fully capture the role of interactions between units in estimating the ATE (see Appendix 3.B). On this basis, we assume linear ATE as

[11] An explanation of the meaning of every panel is in Figure 3.1

Table 3.6. Bias/Efficiency DID with neighbourhood effects

			BIAS			RMSE			DID-estimate		
	n	m	OLS	Spat-DID	SH-DID	OLS	Spat-DID	SH-DID	OLS	Spat-DID	SH-DID
	225		0.0624	0.0451	0.0613	0.1539	0.0567	0.1193	0.0000	0.0173	0.0011
ATE	400	100	0.0625	0.0461	0.0618	0.1096	0.0590	0.0887	0.0000	0.0164	0.0007
	625		0.0606	0.0464	0.0602	0.0852	0.0637	0.0748	0.0000	0.0142	0.0004
	225		0.0622	0.0450	0.0613	0.1495	0.0585	0.1166	0.0000	0.0173	0.0009
ATE	400	250	0.0626	0.0460	0.0619	0.1119	0.0617	0.0911	0.0000	0.0166	0.0007
	625		0.0602	0.0460	0.0596	0.0833	0.0636	0.0736	0.0000	0.0142	0.0005

Legend: Table 3.6 indicates the bias of the ATE in presence of interferences. Columns BIAS indicates the differences between the estimated ATE and the expected value of β_3, columns RMSE represents the Root Mean Square Error, while the columns labeled as DID-Estimate shows the bias of the double differences compared to the estimate of the regression model.

Table 3.7. Results Novel DID with neighbourhood effects

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

Legend: Table 3.7 presents the results of the novel DID model in presence of neighbourhood effects. n represents the number of units (225, 400 and 625), m the number of replications (100 and 225), the columns DID, Spat-DID, SH-DID display, respectively, the results of linear, spatial and hierarchical models, while the last column indicates the true value of the parameter.

Table 3.8. Bias Novel DID with neighbourhood effects

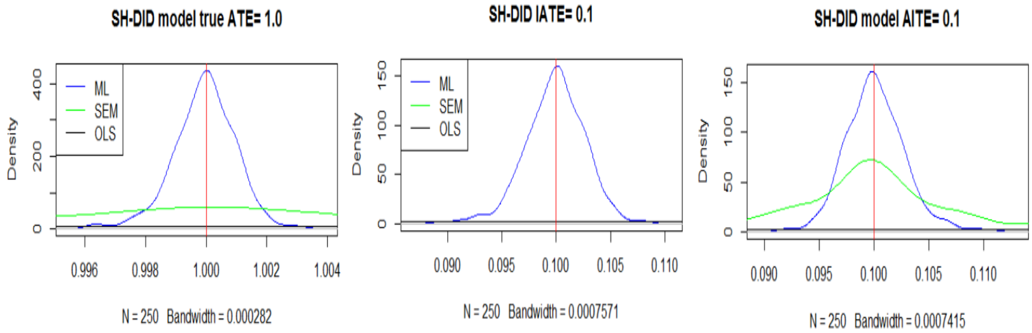
	n	m	BIAS OLS	BIAS Spat-DID	BIAS SH-DID	RMSE OLS	RMSE Spat-DID	RMSE SH-DID
ATE	225	100	0.0117	0.0015	0.0000	0.1395	0.0562	0.1179
AITET			0.0000	0.0190	0.0000	0.1395	0.0562	0.1179
AITENT			0.0320	0.0208	0.0001	0.1395	0.0562	0.1179
ATE	400		-0.0136	-0.0011	-0.0001	0.1032	0.0587	0.0876
AITET			0.0000	-0.0327	0.0000	0.1032	0.0587	0.0876
AITENT			-0.0358	-0.0332	-0.0003	0.1032	0.0587	0.0876
ATE	625		0.0002	-0.0001	0.0000	0.0822	0.0633	0.0731
AITET			0.0000	0.0019	0.0000	0.0822	0.0633	0.0731
AITENT			0.0005	0.0017	-0.0001	0.0822	0.0633	0.0731
ATE	225	250	0.0004	-0.0006	-0.0001	0.1379	0.0580	0.1154
AITET			0.0000	0.0112	0.0001	0.1379	0.0580	0.1154
AITENT			0.0008	0.0097	-0.0002	0.1379	0.0580	0.1154
ATE	400		-0.0063	-0.0002	-0.0001	0.1053	0.0613	0.0896
AITET			0.0000	-0.0107	0.0000	0.1053	0.0613	0.0896
AITENT			-0.0174	-0.0106	-0.0001	0.1053	0.0613	0.0896
ATE	625		-0.0014	-0.0003	-0.0001	0.0805	0.0632	0.0721
AITET			0.0000	-0.0029	0.0000	0.0805	0.0632	0.0721
AITENT			-0.0037	-0.0034	-0.0003	0.0805	0.0632	0.0721

Legend: Table 3.8 indicates the bias of the ATE in presence of interferences. Columns BIAS indicates the differences between the estimated causal effects and their expected value, columns RMSE represents the Root Mean Square Error.

benchmark value to analyse the results of the other estimation procedure. The estimates of the spatial approach are biased and in line with the previous case; whereas the SH-DID provides results similar to the linear model, demonstrating the unbiasedness of this approach in estimating the total effect. Moreover, Table 3.6 shows how RMSE of both multilevel and linear model converges to the one of the spatial approach when sample size and number of replications increase, proving a substantial improvement of the quality of the estimates. The estimates of the novel DID with interferences (Tables 3.7 and 3.8) show better performances of the multilevel approach for all the different sample sizes and number of replications. Moreover, hierarchical model provides unbiased estimates of both direct and indirect effects. This model, controlling for the presence of spatial heteroskedasticity at neighbourhood level, involves a substantial reduction of the standard errors and an improvement of the quality of our estimates. Although multilevel model is an unbiased estimator of the Diff-in-Diffs in presence of interferences, both spatial and linear models reduce their bias for high sample size and number of replications. However, the results presented in Tables 3.5-3.8 indicates the mean value of the parameters over the number of replications considered. Looking at the distribution of the estimated parameters provides further evidences on the unbiasedness and efficiency of the SH-DID.

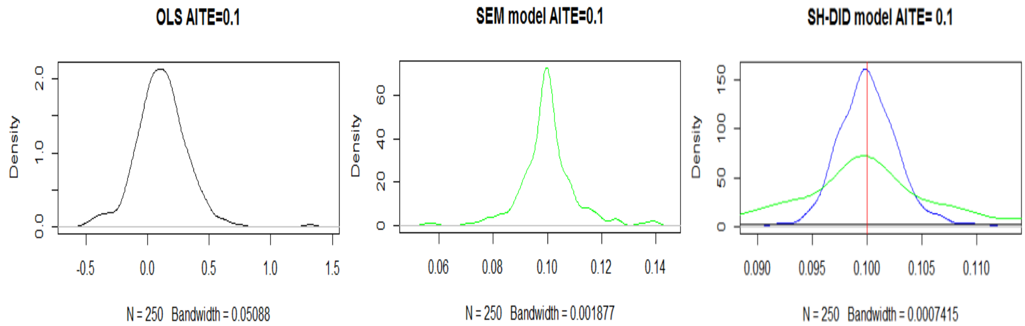
Figure 3.4 shows the distribution of the estimators of the parameters β_3,β_4 and β_6. SH-DID presents better performances compared to the other approaches. The superiority of the hierarchical model can be observed both in terms of unbiasdeness and efficiency. Precisely, the distribution of the SH-DID estimates presents a maximum on the true value of β_3,β_4 and β_6. Moreover, hierarchical approach reveals the less dispersed distribution. Figure 3.5 presents a deeper investigation on the distribution of the parameter β_6. This case is of particular relevance for two distinct reasons. On one hand, β_6 constitutes the parameter of the indirect effects on the treated. On the other hand, it represents the case in which both linear and

Figure 3.4. Density distribution of the parameter



Legend: Figure 3.4 shows the distribution of the parameter β_3,β_4 and β_6. Blue line represents SH-DID, green line the Spat-DID, black line the linear model and the red line the "true" value of the parameter.

Figure 3.5. In-Depth comparison density parameter β_6



Legend:Figure 3.5 highlights the distribution of the parameter β_6 over the Montecarlo simulation. Left panel shows the results for the linear model and the central panel shows the distribution of the spatial model. The right panel compares the distribution of β_6 for the multilevel (blue line), spatial (green line) and linear (black line) approaches.

spatial model has better performances. Notwithstanding Spat-DID provides a satisfying approximation of the real value of β_6, it presents less efficient estimates in comparison with SH-DID. To conclude, the SH-DID allows to recombine in a unique framework the estimation of total, direct and indirect treatment effects when we introduce the presence of spatial interferences.

3.4 Conclusions

In this paper we present an alternative DID procedure that considers the presence of spatial interferences. This paper aims to demonstrate the correctness of the ATE estimated by "traditional" method even in presence of interferences. However, the development of an alternative approach is required taking into account the inability of obtaining an unbiased decomposition of the ATE into direct and indirect effects. For this reason, we produce 2 different cases in order to find the optimal estimation procedure. The first case considers the presence of spatial heterogeneity comparing the performances of a linear and a spatial model. The results are ambiguous and do not permit to identify the optimal solution. Linear model provides correct estimates of the ATE, while the spatial model produces unbiased estimates of the direct and indirect effects. The introduction of neighbourhood effects and an alternative hierarchical modelling allows to overcome the ambiguity in the choice of the preferable methodology in presence of interferences between units. In fact, the multilevel estimation procedure presents unbiased and more efficient estimates both for total, direct and indirect effects. The results are in line with a part of the literature that suggests the use of hierarchical model to deal with the identification problems in presence of spatial heterogeneity (Corrado and Fingleton, 2011, 2012).

APPENDIX

3.A Proofs of treatment effects

In this section we demonstrate the formulation of total, direct and indirect effects obtained with the novel Diff-in-Diffs with interferences estimator. Recalling the equation (7), this model is defined as:

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

The presence of interactions between units is considered by the inclusion of an additional variable which, for each agents, represents the state of treatment of neighbours' units. In detail, D_j allows to control for the presence of heterogeneity on the interaction between own and neighbours treatment ($D_j D$) and estimate the temporal trends in response of both neighbours state of treatment ($D_j t$) and the interaction between own and neighbours treatment ($D_j Dt$). In first instance, we demonstrate the formulation of the "traditional" ATE:

$$\begin{aligned}\textbf{ATE} =& E[Y|D=1,T=1] - E[Y|D=1,T=0] - [E[Y|D=0,T=1] - E[Y|D=0,T=0]] = \\ & (\beta_0 + \beta_1 + \beta_2\beta_3 + \beta_4\overline{D_j^1} + \beta_5\overline{D_j^1} + \beta_6\overline{D_j^1} - \beta_0 - \beta_1 - \beta_5\overline{D_j^1}) - (\beta_0 + \beta_2 + \beta_4\overline{D_j^0} - \beta_0) = \\ & \beta_3 + \beta_4(\overline{D_j^1} - \overline{D_j^0}) + \beta_6\overline{D_j^1}\end{aligned}$$

The ATE is a composite parameter of direct and indirect effects. The definition of these effects recalls the one proposed by Hudgens and Halloran (2012). The direct effect is the response of the individual to the treatment. We estimate the direct impact with a Diff-in-Diffs estimator in the case in which the units do not have any neighbours treated. On the other hand, the indirect effects are defined as the response of the individuals to the interferences. Our approach starts from the idea that can exists differentiated impact of the interactions on treated and controls. In this way, we isolate the indirect effect with a Diff-in-Diffs estimator conditioning on time and on the level of interferences, maintaining constant the treatment group.

$$\begin{aligned}\textbf{ADTE} =& [E(Y|D=1,t=1,D_j=0) - E(Y|D=1,t=0,D_j=0)] - [E(Y|D=0,t=1,D_j=0) - \\ & E(Y|D=0,t=0,D_j=0)] = (\beta_0 + \beta_1 + \beta_2 + \beta_3 - \beta_0 + \beta_1) - (\beta_0 + \beta_2 - \beta_0) = \beta_3\end{aligned}$$

$$\begin{aligned}\textbf{AITET} =& E[(Y|D=1,t=1,D_j\neq 0) - E(Y|D=1,t=0,D_j\neq 0)] - [E(Y|D=1,t=1,D_j=0) - \\ & E(Y|D=1,t=0,D_j=0)] = [\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4\overline{D_j^1} + \beta_5\overline{D_j^1} + \beta_6\overline{D_j^1} - (\beta_0 + \beta_1 + \beta_5\overline{D_j^1})] - \\ & [\beta_0 + \beta_1 + \beta_2 + \beta_3 - (\beta_0 + \beta_1)] = \beta_4\overline{D_j^1} + \beta_6\overline{D_j^1}\end{aligned}$$

$$\mathbf{AITENT} = E[(Y|D=0,t=1,D_j \neq 0) - E(Y|D=0,t=0,D_j \neq 0)] - [E(Y|D=0,t=1,D_j=0) - E(Y|D=0,t=0,D_j=0)] = (\beta_0+\beta_2+\beta_4\overline{D_j^0}-\beta_0) - (\beta_0+\beta_2-\beta_0) = \beta_4\overline{D_j^0}$$

Recombining direct and indirect effects we can recover the ATE.

3.B Proof of the Unbiasedness of the Decomposition Process of the ATE

To demonstrate the unbiasedness decomposition of the ATE estimated by the linear model we report the results of one simulation. In detail, the estimates are referred to the case of 100 simulation and 225 units with spatial heterogeneity[12]. From the simulation we obtain:

- ATE=1.0525
- $\overline{D_j^0} = 0.2657$
- $\overline{D_j^1} = 0.3954$

Taking into account the DGP, we expect direct and indirect effects equal to:

- $E(ADTE) = \beta_3 = 1$
- $E(AITET) = (\beta_4+\beta_6) * \overline{D_j^1} = 0.2 * 0.3954 = 0.0791$
- $E(AITENT) = \beta_4 * \overline{D_j^0} = 0.1 * 0.2657 = 0.0266$

Recalling ATE definition, we recompose the overall effect as the sum of direct and indirect effects in the following way:

$$\underbrace{ATE}_{\beta_3+\beta_4(\overline{D_j^1}-\overline{D_j^0}+\beta_6)\overline{D_j^1}} = \underbrace{ADTE}_{\beta_3} + \underbrace{AITET}_{(\beta_4+\beta_6)\overline{D_j^1}} - \underbrace{AITENT}_{\beta_4\overline{D_j^0}} = 1+0.0791-0.0266 = 1.0525$$

Q.e.d., the decomposition process provides an unbiased estimator of the ATE and corresponds to the results of the linear model.

[12]This case is reported as example. However, the demonstration of the correctness of linear estimator is possible for all the other considered circumstances.

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Chapter 4

SH DID: An Empirical Application

4.1 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 manners 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 idea take 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 perspective,

[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).

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 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 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[3](Rubin, 1980). As previously discussed, 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. However, SUTVA does not allow a correct identification and estimation of the indirect treatment effects.
Moreover, the development of place-based policies targeted to the formation of spatial and social linkages between economic agents and the necessity to evaluate the effects of the interferences makes the SUTVA a streamlined and 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 chapter we provide an in-depth analysis of the literature focuses on the violation of the "no-interferences" assumption. Moreover, 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. In this way, it is possible to estimate direct and indirect effects by decomposing the ATE.

4.2 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,

[3]The value of the outcome for unit i when exposed to treatment t will be the same regardless of the treatments that other units receive (Rubin, 1974).
[4]See Zúñiga-Vicente et al. (2014) and Becker (2015) for recent survey on policy evaluation studies. The relevance of this theme for the Italian case is remarked by Caloffi et al. (2016).

meanwhile they consider the *"indirect effect"* as the response to the interferences. Under this perspective, interactions between units have a twofold relevance. On the one hand, they make possible the identification of correct total effects of the treatment. Conversely, the presence of interferences in a causal framework is essential in the case in which treatment induces interactions. However, a straightforward inclusion of interferences in causal analysis is not possible.

Rosenbaum (2012) highlights the difficult specification and the potential boundless extent of the interferences. Specification problem is addressed by modelling interferences with 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 hierarchical and spatial econometrics approaches enable to deal with the reflection problem. Theoretical and empirical analyses considering the potential outcomes framework and its associated assumptions in a spatial context are still few and far between (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 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)[5]. 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.

4.3 Empirical Strategy

4.3.1 Public Policies

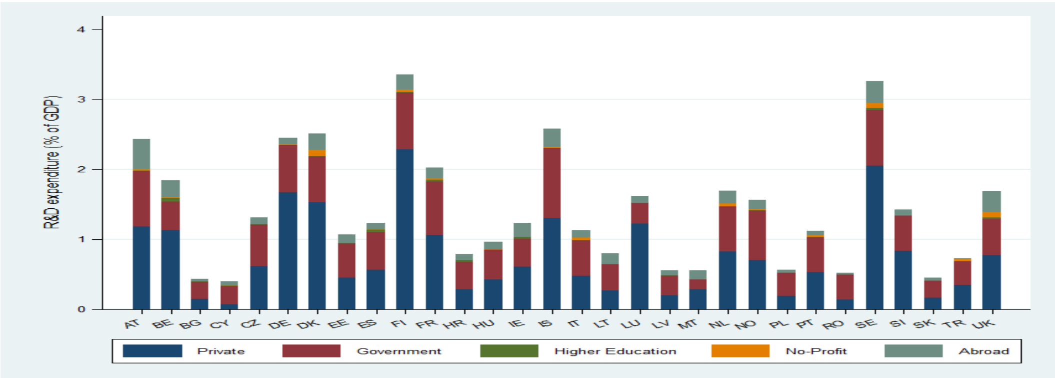
In recent years, Eu Commission underlines the relevant role played by R&D and innovation to foster growth. Notwithstanding, public and private R&D expenditures remain stable over the last decade and distant from the 3% objective specified in the Horizon 2020 plan.

Figure 4.1 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 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.
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 4.2 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

[5] The approach presented in Chapter 3.

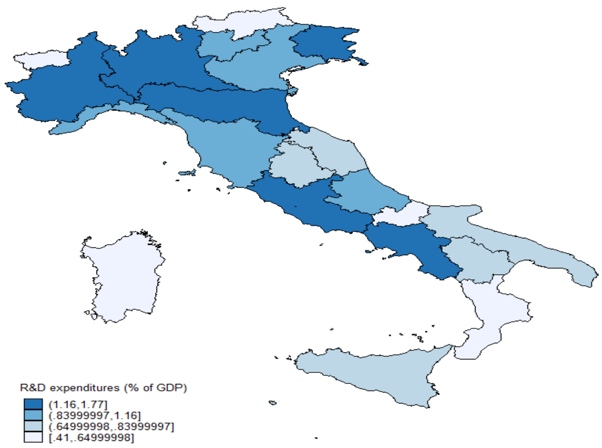
Figure 4.1. European R&D Expenditures by source of funds



Source: Eurostat

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

Figure 4.2. 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.

exhibit, on average, lower level of R&D expenditures. The development gap between North and South does not affect only R&D expenses. Moreover, structural differences can also be found in regional economic accounts and employment rate and are considered as one of the major weakness of Italian economic system (MISE, 2015).
The lack of R&D investments and the territorial development gap makes necessary 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 [6].

Table 4.1. 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.

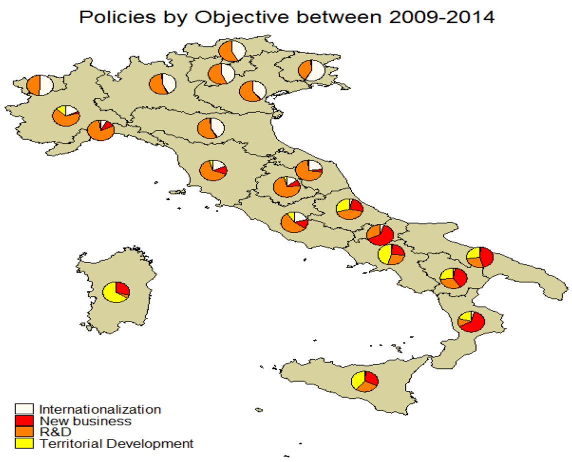
Table 4.1 resumes the total amount of public funding in Italy between 2007-2013. The country-wide financial commitment consists of €60 billion, fairly subdivided between European and National funds. On the whole, Italy has defined 66 programmes:

- 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.

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

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. Italy allocate €9.6 billion to this priority, in particular through the "Research and Competitiveness" programme.

Figure 4.3. Objective of public policies



Note: Figure 4.3 shows the different objectives of the public policies distinguished by Region.

Figure 4.3, analysing the different objectives followed by the policies, remarks the structural differences between Northern and Southern Regions. The firsts are subjects to policies promoting 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.

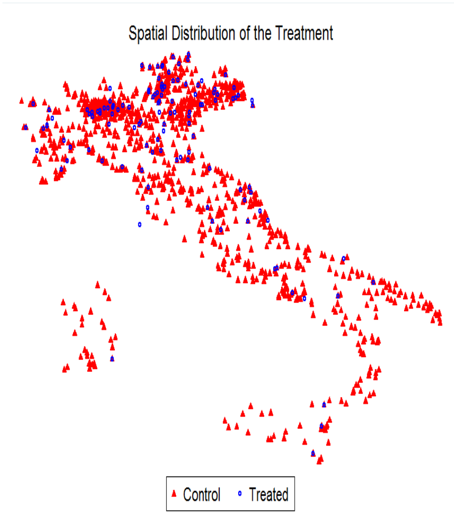
4.3.2 Data

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[7] (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 the dataset requires a preparatory identification of the firms participating to

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

both CIS waves.
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 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[8]. Conversely, the correct identification of a pre and post treatment period required the exclusion from the sample of all the firms subsidized on 2008 or on both periods, reducing the sample size to 2389 SMEs of which only 145 treated.

Figure 4.4. Spatial Distribution of the firms



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

Figure 4.4 shows the geographical localization of the firms. The majority of the units are located in the north of the Italy, 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.

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

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

Table 4.2. 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)

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 testing a novel framework able to include spatial interferences in causal analysis, an additional control is required. In detail, we need to analyse if the spatial distribution of the treatment variable is 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.

Table 4.3. 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

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 (2016b).

4.3.3 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.

$$y_i = D_i y^1 + (1 - D_i) y^0 = \begin{cases} y^1 & \text{if } D = 1 \\ y^0 & \text{if } D = 0 \end{cases} \tag{4.1}$$

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.

$$y = Dy^1 + (1 - D)y^0 + D_j(Dy^1 + (1 - D)y^0) - D_j(Dy^1 + (1 - D)y^0) \tag{4.2}$$

The POM in 4.1 corresponds to the equation in 4.1 plus/minus 4.2 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, 4.2 can be rearranged as:

$$y = \underbrace{(1 - D_j)(Dy^1 + (1 - D)y^0)}_{\text{Effect without interactions}} + \underbrace{D_j(Dy^1 + (1 - D)y^0)}_{\text{Effect interactions}} \tag{4.3}$$

Under the formulation in 4.3 we are able to identify both direct and indirect effects. More specifically, the first term in 4.3 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 4.4.

$$ATE = ADTE + AITE = (1 - D_j)ATE + D_j ATE \tag{4.4}$$

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:

$$Y = \beta_0 + \beta_1 D + \beta_2 T + \beta_3 DT \tag{4.5}$$

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

$$\begin{aligned} a_S &= E[Y|D=1,T=1] = \beta_0+\beta_1+\beta_2+\beta_3 \\ b_S &= E[Y|D=1,T=0] = \beta_0+\beta_1 \\ c_S &= E[Y|D=0,T=1] = \beta_0+\beta_2 \\ d_S &= E[Y|D=0,T=0] = \beta_0 \\ ATE &= (a_S-b_S)-(c_S-d_S) = \beta_3 \end{aligned} \tag{4.6}$$

4.5 and 4.6 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 4.5 adapting the line of reasoning in 4.2. In other words, we include an additional part in the "standard" DID multiplied by D_j to model the presence of spatial interactions.

$$Y = \beta_0+\beta_1 D+\beta_2 t+\beta_3 Dt+\beta_4 D_j t+\beta_5 D_j D+\beta_6 D_j Dt \tag{4.7}$$

The specification in 4.7 allows to estimate simultaneously total, direct and indirect causal effects. Implementing the "standard" Diff-in-Diff approach to 4.7 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:

$$ATE = \beta_3+\beta_4(\overline{D_j^1}-\overline{D_j^0})+\beta_6\overline{D_j^1} \tag{4.8}$$

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 4.8 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.

$$\begin{aligned} &a = E[Y|D=1,t=1,D_j\neq 0] = \beta_0+\beta_1+\beta_2+\beta_3+\beta_4\overline{D_j^1}+\beta_5\overline{D_j^1}+\beta_6\overline{D_j^1} \\ &b = E[Y|D=1,t=1,D_j=0] = \beta_0+\beta_1+\beta_2+\beta_3 \\ &c = E[Y|D=1,t=0,D_j\neq 0] = \beta_0+\beta_1+\beta_5\overline{D_j^1} \\ &d = E[Y|D=1,t=0,D_j=0] = \beta_0+\beta_1 \\ &e = E[Y|D=0,t=1,D_j\neq 0] = \beta_0+\beta_2+\beta_4\overline{D_j^0} \\ &f = E[Y|D=0,t=1,D_j=0] = \beta_0+\beta_2 \\ &g = E[Y|D=0,t=0,D_j\neq 0] = \beta_0 \\ &h = E[Y|D=0,t=0,D_j=0] = \beta_0 \end{aligned} \tag{4.9}$$

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 4.10:

$$ADTE = b - d - f + h = \beta_3 \tag{4.10}$$

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.

$$AITET = a - c - b + d = \beta_4 \overline{D_j^1} + \beta_6 \overline{D_j^1} \tag{4.11}$$

$$AITENT = e - g - f + h = \beta_4 \overline{D_j^0} \tag{4.12}$$

4.11 and 4.12 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.

4.4 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)[9]. The choice of these variables is adherent for obtaining detailed information on the process of production of innovation and

[9] 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.

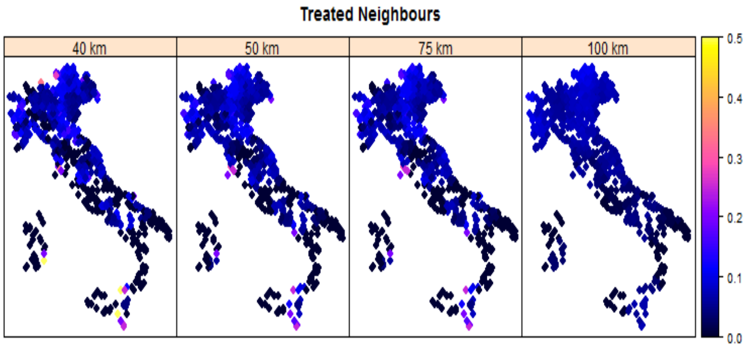
R&D.
To ensure robust and unbiased estimates of both direct and indirect effects we follow the approach in Di Gennaro and Pellegrini (2016b). The aforementioned authors demonstrate how the linear model is an unbiased estimator only of the ATE. Indeed, the linear approach is not able to adequately distinguish 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 ($D_j Dt$).
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. 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. This procedure permits to obtain information on their optimal dimension over the space.

Figure 4.5 analyse the share of neighbours treated for all the firms included in our analysis along 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

Figure 4.5. 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.

low share of treated neighbours (dark blue). Conversely, increasing cut-off distances implies a reduction, on average, 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[10]. This relation is deepened in the discussion of the results.

[10]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.

Table 4.4. Results

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

		OUTCOME														
		External R&D					Other R&D					Total R&D per Employee				
		[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
40	Dt	43571.4**	214291***	233369.0***	214361.9***	231258.3***	81401.1**	129136.3*	130485.3**	129689*	125453.1**	534.10	3776.5	5446.4**	3829.1	5240.2**
		[18674.5]	[35163.8]	[28265.1]	[34677.0]	[28017]	[36528.7]	[69370.1]	[55755.7]	[69024.5]	[55612.7]	[1698.1]	[3222.7]	[2590.5]	[3211.6]	[2586.5]
	Djt		-808.9	-808.9	417.5	3625.6		5812.5	5812.5	15205.3	14646.2		21.0	21.0	911.1	1071.0
			[71180.5]	[71179.3]	[79494.9]	[79413.7]		[140422.7]	[140408.0]	[150123.7]	[150030.6]		[6523.6]	[6523.5]	[6905.1]	[6901.8]
	DjDt		-2669435.3***	-2967750***	-2670661.8***	-2935048.8***		-746749.1	-767842.7	-756141.9	-689876.3		-50701.7	-76814**	-51591.8	-73665.8**
			[468008]	[334731.4]	[462070.9]	[333574.3]		[923271.4]	[660290.1]	[919263.6]	[660257.1]		[42892.5]	30677.6	[42767.0]	[30692.2]
50	Dt	43571.4**	266426.9***	312577.3***	266711.8***	309128.9***	81401.1**	-25849.7	46913.6	-24773.2	39209.0	534.10	667.9	6269.7**	758.9	5887.6**
		[18674.5]	[40698]	[31816.7]	[40177.8]	[31595.9]	[36528.7]	[80545.0]	[62960.2]	[80171.6]	[62825.1]	[1698.1]	[3740.6]	[2925.1]	[3729.5]	[2921.7]
	Djt		-3767.2	-3767.2	1044.6	9098.7		-100169.0	-100169.0	-82020.1	-73729.2		-707.1	-707.1	824.5	1381.1
			[85852.9]	[85873.7]	[98263.6]	[98213.7]		[169910.9]	169930.4	[184312.9]	[184210.8]		[7890.9]	[7894.8]	[8440.9]	[8447.4]
	DjDt		-3291078.3***	-3972703.5***	-3295890***	-3923281.3***		1595323.4	520633.6	1577174.5	631246.6		-1896.8	-84634.2**	-3428.5	-79240**
			[537178.9]	[384756.3]	[531189.8]	[383906.6]		[1063126.3]	[761371.8]	[1059152.4]	[761272.6]		[49373.2]	[35372.8]	[49262.2]	[35385.9]
75	Dt	43571.4**	234632.4***	304077.7***	235739.4***	299538***	81401.1**	-54014.7	76947.6	-52150.4	66348.2	534.10	383.8	9099.8***	443.6	8575.9**
		[18674.5]	[49384.6]	[37571.5]	[48774.3]	[37297.5]	[36528.7]	[97270.3]	[73999.6]	[96853.3]	[73856.5]	[1698.1]	[4515.7]	[3437]	[4503.4]	[3433.8]
	Djt		-6423.9	-6423.9	12166.8	27227.5		-56661.8	-56661.8	-25241.0	-8481.8		1865.1	1865.1	2882.8	3810.5
			[103627.5]	[103667.6]	[122594.3]	[122463]		[204109.8]	[204180.3]	[225247.2]	[225127.8]		[9475.5]	[9483.3]	[10270.5]	[10280.9]
	DjDt		-2837161.3***	-3868651.3***	-2855752***	-3805058.3***		2017724.0	72505.6	1986303.3	224331.6		2023.2	-127438.2***	1005.5	-119890.5***
			[681521]	[487635.6]	[674194]	[485573.7]		[1342356.8]	[960431.4]	[1337744.4]	[959891.9]		[62317.2]	[44608.0]	[62189.9]	[44613.6]
100	Dt	43571.4**	398763.8***	487814.4***	397758.0***	481707.7***	81401.1**	216516.3*	326576.2***	219294.1*	307179.6**	534.10	4888.7	16749.7***	4980.6	15946.1**
		[18674.5]	[61876.7]	[45944.3]	[61120.9]	[45726.0]	[36528.7]	[122405.4]	[90861.1]	[121901.9]	[90837.4]	[1698.1]	[5680.1]	[4219.8]	[5665.5]	[4221.6]
	Djt		814.3	814.3	-16002.9	5095.8		82055.2	82055.2	128905.6	141575.6		4159.4	4159.4	5718.6	6992.3
			[117995.5]	[118040.2]	[143367.4]	[143141.3]		[233420.6]	[233440]	[261834.4]	[261697.2]		[10831.6]	[10841.5]	[11880.0]	[11906.3]
	DjDt		-5262002.5***	-6581219.5***	-5245185.5***	-6491314.5***		-2011266.8	-3641720.8***	-2058117.0	-3361561.8***		-64998.7	-240710.4***	-66557.8	-229153.4***
			[876711.5]	[625754.9]	[867173.3]	[624117.1]		1734324.8	[1237513.9]	[1728412]	[1238417.5]		[80479.2]	[57472.9]	[80317.3]	[57541.9]

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

List of approach
[1] Traditional DID
[2] Linear DID with Interferences, complete model
[3] Linear DID with Interferences, alternative specification without control for $D_j D$
[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 are calculated by different cut-off distances: 40 km, 50 km, 75 km, 100 km

Firstly, we analyse the total impact of the treatment (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 results provides evidence on the additionality on R&D expenses. Moreover, the ATE estimated in model 1 constitutes the benchmark for the decomposition process proposed with the alternative Difference in Difference models[11].
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 neighbours treated.
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 4.5 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. The analysis of the paths followed by the decomposition process open up two distinct considerations.
On the one hand, the complete models (i.e. 2 and 4) shows equal estimates of the AITET, but differentiated results for ADTE and AITENT. As explained above, this is mainly due to the different estimation procedures. Indeed, linear model does not correctly distinguish between different indirect effects, even if it is able to catch unbiased ATE estimates. Instead, hierarchical model is a good approximation of both total, direct and indirect effects and, on the whole, the SH-DID model produces unbiased and more efficient estimates. This

[11] 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 4.5. Decomposition of the ATE

			40				50				75				100			
			ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE	ADTE	AITET	AITENT	ATE
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
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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

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, 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.

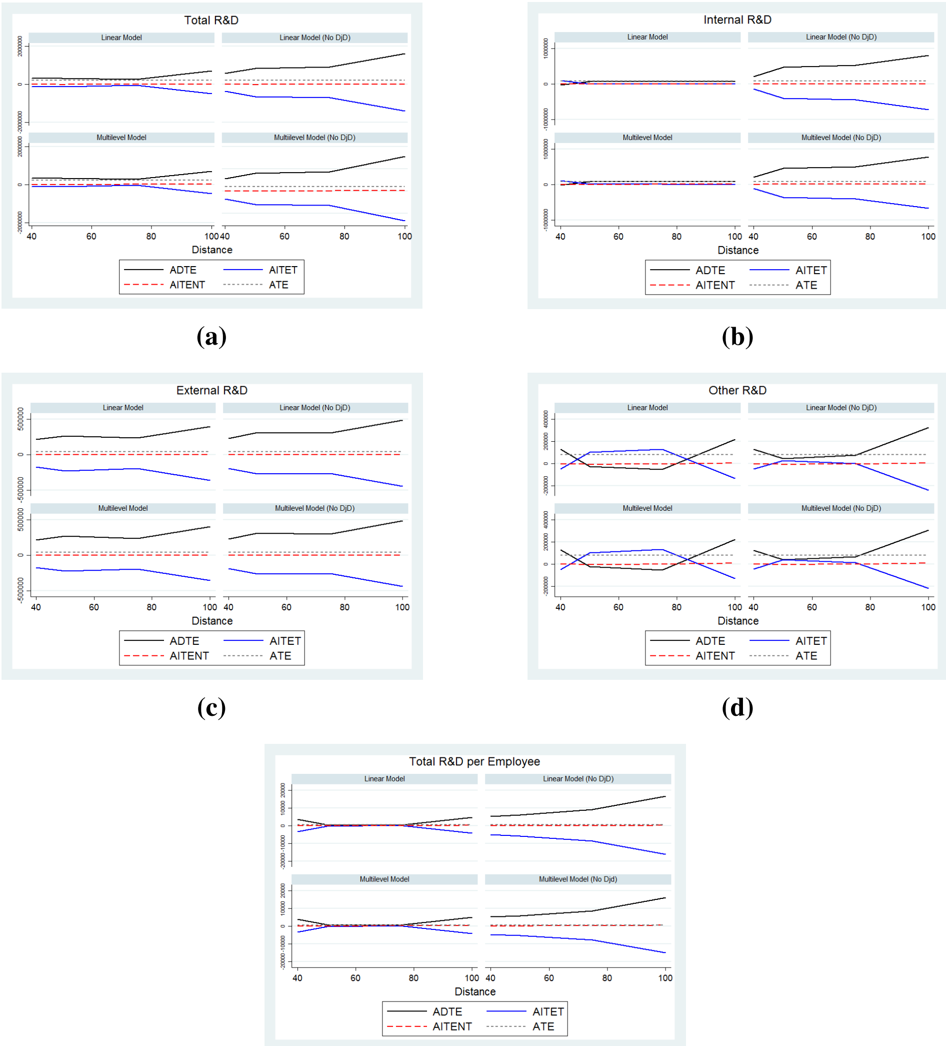
4.5 Conclusions

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 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[12]. Furthermore, this chapter demonstrates the role of distance in estimating the spatial extension of both direct and indirect effects.

Figure 4.6. 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.

Figure 4.6 resumes the behaviour of treatment effects over space. Focusing on ADTE trend,

[12] 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.

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

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

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.

Chapter 5

Conclusions

This thesis has discussed the role played by interactions between units in a causal framework. The presence of interferences has a twofold impact on causal effects. On one hand, it can allows to estimate spillover, or indirect, effects. Conversely, it has required a substantial review of ”traditional” causal framework. Indeed, the golden standard in causal analysis is represented by the so-called Rubin Causal Model (Rubin, 1974, 1977; Rosenbaum and Rubin, 1983).
This approach, relying on the validity of the SUTVA, explicitly assumes the absence of interferences between units(Cox, 1959). In this sense, in Chapter 1 we propose an in-depth analysis on the problems related to the inclusion of interferences in estimating causal effects. Moreover, we demonstrate, in a methodological way, how hierarchical and spatial techniques can address identification problems(Corrado and Fingleton, 2012; Gibbons et al., 2014).
This thesis is deeply-rooted in this perspective. A recap of the main innovations and findings presented in this work is nevertheless required. Recalling the initial summary, the thesis laid out 4 distinct objectives resumed in 4 different research questions. During the remainder of this chapter we will reply, separately, to every question, highlighting the main contributions proposed in this dissertation.

How we can include spillover effects in causal analysis?

This question has required a substantial review of causal framework. In this sense, we suggest two different approaches in modelling the presence of interferences in causal analysis. The common feature of both approaches is constituted by the modification of a traditional Difference-in-Differences estimator.
The first method[1] restricts the validity of the SUTVA. This hypothesis allows to take into

[1] see Chapter 2

account geographical localization and market concentration. In detail, we have defined the more developed areas in Umbria, assuming that the location in these areas can have an impact on the effectiveness of regional policies. The second stage of this analysis consists in imposing a restriction on the validity of the SUTVA. Moreover, we assume that interferences are limited within developed and underdeveloped areas.
In this way, we explicitly rule out the presence of interferences between the areas. This assumption allows to modify the Diff-in-Diff model to take into account geographical localization. To summarize, we define two additional treatment effects on the basis of geographical location of controls units, the ATEIC and the ATEUC. The ATEUC represents the impact of the subsidies, taking into account the interferences; the ATEIC is a measure of the error in the estimation of the effects when we wrongly assume the validity of the SUTVA. However, the difference between ATEUC and ATEIC provides a measure of the spillover effects in response of the subsidies.
The second approach modifies the DID model by including the presence of interferences in its regression model. The idea behind this methodology is based on the adjustment of the ”traditional” potential outcome framework. In this way, we are able to decompose the ATE in direct and indirect effects. Translating this intuition in a DID framework we provide three distinct treatment effects (ADTE, AITET and AITENT).
The ADTE (Average Direct Treatment Effect) represents the situation in which there are not interactions due to the treatment. The AITET (resp. AITENT) provides an estimate of the indirect effects on the treated (resp. not treated) in response to the interferences.

What is the dimension of proximity more adaptable to causal context?

Boschma (2005) proposes a classification of the role covered by different typologies of proximity (cognitive, organizational, social, institutional and geographical) in diffusing innovation. Notwithstanding the relevance of the different typologies, in this thesis we consider only the spatial dimension of the proximity. This choice is justified in consideration of the subject of our analysis.
Indeed, the proposed approaches are deeply-rooted in a policy evaluation context. Recent policies tend to stimulate innovation and growth by creating linkages between the different economic agents. Moreover, empirical literature demonstrate a greater effectiveness for the SMEs (see Merito et al. (2007); Bronzini et al. (2008) inter alia).
In this context, it seems reasonable to assume that interferences are influenced by geographical proximity. Furthermore, spatial closeness can provides a good approximation also of the social proximity. Despite this, the inclusion of alternative dimension of proximity will become an interesting topic for further research. The opening to different typologies of proximity allows a disclosure of our novel methodologies to different fields, including

labour, health, education, etc.

Is it possible to identify both direct and indirect effects?

Hudgens and Halloran (2012) propose a definition of direct and indirect effects. The first is the response of the individuals to a treatment, while the latter represents the response to the interferences between units. The identification of the indirect, or spillover, effects requires the determination of an appropriate measure to approximate interferences. In the case of SH-DID we use the state of treatment of neighbours units. This hypothesis can be considered the optimal solution in a policy evaluation context. Indeed, our approach aims to estimate the effects of interferences in response to treatment.
Notwithstanding, different functions can be considered, including nodal distance between points in a network, social-economic indicators, geographical distance, etc. In this sense, combining different proximity function to obtain a more robust approximation of interactions between units can be a topic for further researches on this theme.
After having defined the interferences, it is possible to identify and estimate direct and indirect effects. Following the definition in Hudgens and Halloran (2012), we estimate the direct effect applying a double-differences in time and state of treatment for the units without treated in their neighbourhood. In other words, the direct impact of a policy constitutes the quota of total effect polished by the presence of interferences. Indirect effects constitutes the residual part of the ATE (see Equation 3.3). In detail, SH-DID model provides estimates of indirect effects by double-differencing over time and state of treatment of the neighbours.

Is ATE, in presence of interferences, biased?

This question is the most important issue raised up in this thesis. Montecarlo simulations of SH-DID model provides satisfying evidences in favour of the unbiasedness of the ATE, even in presence of interferences. Do not consider direct and indirect effects in a setting where interferences are included does not allow to fully comprehend ATE. In this sense, the decomposition of the ATE presented in the SH-DID model makes the researcher able to estimate simultaneously total, direct and indirect effects.
Moreover, comparing the results of three different estimation procedure (linear, spatial and spatial hierarchical approaches) we propose a unique methodological framework to provide unbiased estimates of the ATE and its components. The best-fitting procedure is represented by the Spatial Hierarchical DID model.
The unbiasdeness of the ATE even in presence of interferences requires an additional consideration. This result does not invalidate the validity of traditional causal model. Nevertheless, it highlight the need of modifying traditional causal methodologies in order to take into

account the presence of interferences. In this sense it is possible to underline an additional idea for future research. In fact, the causal framework proposed in this thesis can be easily adapted to other methodologies and can constitute an initial step to a review of the traditional approaches in causal analysis.

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