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The network effects of regional R&D collaboration policy

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Abstract

Adopting a counterfactual approach to the evaluation of an R&D collaboration policy, carried out on a regional scale, we investigate different types of persistent network effects, namely persistence, breadth, composition, and intensification. Our findings reveal that the R&D collaboration policy was able to generate a persistent change in the networking behaviour of participating firms (persistence effect), stimulating in particular collaborations with universities. Network effects were greater for firms that, prior to the policy intervention, were already accustomed to collaborating, than for more stand-alone firms. With respect to the former firms, we also find a composition effect, which implies a change in the type of partners in innovation-related activities.

Key words: Network additionality, network persistence, policy evaluation, R&D collaboration policy.

JEL code: O38, O32, D04,

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1. Introduction

The past two decades have witnessed the spread of innovation policies that attempt to foster innovation by encouraging interactions among organizations with different knowledge and competencies (Mowery, 1994; Metcalfe and Georghiou, 1997; Georghiou, 2002; Autio et al., 2008), primarily by providing funds for the implementation of R&D collaboration projects. Although the primary objective of these interventions is to promote R&D, their instrumental objective is clearly that of stimulating networking among firms, and among firms and other knowledge-intensive organizations like KIBS (knowledge-intensive business services) and universities. Networking can provide a fertile ground for the development of innovations, and even for the establishment of a regional innovation system or other kinds of innovation system (e.g. platforms, hubs) that can support regional spillovers and innovation (Asheim et al., 2003; Capello, 2009). Many interventions implemented on a regional scale have targeted small and medium-sized enterprises (SMEs), which, despite their pressing need for sourcing external knowledge, have limited resources to invest in the screening and identification of partners to collaborate with (Davenport et al., 1998; Bougrain and Haudeville, 2002; Narula, 2004).

In order to address the emerging problem of how to analyze and evaluate these policies, a growing number of studies have attempted to measure their network or collaboration additionality, or network effects. This concept refers to the ability of a policy intervention to stimulate learning processes that result in changes in the network of participating organizations during and/or after the project's implementation (Davenport et al., 1998; Luukkonen, 2000; Fier et al., 2006; Autio et al., 2008; Clarysse et al., 2009; Afcha Chávez, 2010; Wanzenböck et al., 2013; Knockaert et al., 2014). Indeed, it is important to investigate whether and to what extent firms have learned how to better collaborate with other organizations, as a result of their participation in collaborative R&D policies.

Existing evaluations of collaborative R&D policies have focused on the simultaneous network effects of the interventions. That is, literature has analyzed whether the policies have induced firms to collaborate with new organizations (other than those with which they already collaborated before the policy intervention) during the course of the funded projects (Davenport et al., 1998; Luukkonen, 2000; Caloffi et al., 2015) or whether they have induced firms not previously engaged in R&D collaborations to participate in collaborative R&D projects (Afcha Chavéz, 2010; Wanzenböck et al., 2012). However, evidence on the persistent network effects of collaborative R&D policies is still lacking. The only contribution taking a step in this direction is the seminal work by Fier et al., (2006), which shows that industry/university R&D collaborations that begin with a funded project are likely to end once public funding is withdrawn.

Our paper fills this gap by exploring empirically the ex-post network effects of collaborative R&D policies. We also go beyond current research by untangling different types of network effects that policy participants can experience after the end of the funded project, which we test empirically: i) a *persistence effect*, which occurs when firms continue to collaborate with external organizations; ii) a *breadth effect*, which refers to an increase in the breadth of firms' networks (firms create relationships with organizations with which they did not have any prior connections); iii) a *composition effect*, which occurs when firms change the type of organizations with which they collaborate; and, iv) an *intensification effect*, which refers to a change in the intensity of collaborations (or network depth).

While previous evidence on network effects has been mainly descriptive, we use a propensity score matching approach (Rosenbaum and Rubin, 1983) to make inferences on a set of original data that we have collected through an ad hoc survey. The paper is organized as follows. Section 2 puts forward some hypotheses about how participation in a collaborative R&D policy intervention can induce firms to learn more about networking, and what are the likely consequences for their subsequent propensity for networking. Section 3 illustrates the empirical context in which we tested our hypotheses, which is a regional collaborative R&D policy implemented in the Italian region of Tuscany between 2002 and 2008 using European Regional Development Fund (ERDF) contributions. Section 4 explains the empirical strategy that we adopted for the analysis of this policy, and section 5 presents data and variables. Section 6 presents and discusses the results. Section 7 concludes with some implications for policy and management, and with some proposed avenues for further research.

2. Collaborative R&D policies and their persistent network effects

To build a logical cause-effect chain that could guide us in the empirical analysis of the persistent network effects generated by collaborative R&D policies, we drew on recent studies concerning the learning capabilities of organizations (Clarysse et al., 2009; Knockaert et al., 2014; Roper and Dundas, 2016; Chapman and Hewitt-Dundas, 2016), which refer to the concepts of organizational learning by experience (Cyert and March, 1963), interaction with external organizations (Huber, 1991; Levinson and Asahi, 1996; Kogut, 2000) and absorptive capacity (Cohen and Levinthal, 1998, 1990). In addition, we also consider the cumulative effects of learning (Van den Bosch *et al.* 1999) and networking (Gulati, 1995; Powell et al., 1996; Walker et al., 1997; Chung et al., 2000).

In order to source new knowledge through networking with external organizations, firms must possess a range of knowledge and capabilities with which to value, interpret and absorb flows of information and knowledge that come from outside (Cohen and Levinthal, 1989, 1990). Policies can play an important role in this process since, by participating in collaborative R&D projects, firms perform two types of activities that can have an influence on their networking abilities: they perform R&D and they engage in networking.

By performing R&D, firms can learn how to interpret, manipulate, and internalize external knowledge (Cohen and Levinthal, 1989, 1990). This can increase the expected return on future collaborations, and thus the firm's likelihood of entering into future collaborations (Powell *et al*., 1996; Lane and Lubatkin, 1998; Lane *et al*., 2006; Escribano *et al*., 2009; Huang and Yu, 2011). Thanks to networking, firms can learn how to manage interorganizational relationships through experience and interaction (Cyert and March, 1963; Huber, 1991; Kogut, 2000). In the course of collaborative R&D projects, firms' managers may create or strengthen the appropriate interfaces and routines with which to exchange information and knowledge with the outside, and other staff can learn how to use and modify these interfaces and routines (Van den Bosch et al., 1999; Tierlinck and Spithoven, 2013).

Since organizations learn on the basis of the knowledge that they already possess and of the routines that are in place (Cohen and Levinthal, 1989, 1990; Van den Bosch *et al*. 1999), the new organizational structures and the new knowledge and competencies that have been sourced through interactions with other organizations can improve firms' ability to interact and to learn from interactions, thus increasing the likelihood that they will enter into further relationships once the collaborative R&D project has been completed. Therefore, drawing on the above, we put forward our hypothesis H1.

H1: Participation in a publicly-funded collaborative R&D project increases firms' willingness to engage in subsequent innovation-related interactions with external organizations.

However, R&D collaboration policies do not usually aim to stimulate networking in general terms. Very often, these policies aim to facilitate technology transfer processes or to promote interactions with knowledge-intensive organizations such as universities or other research centers (Cunningham and Gök, 2016). In many cases, these networks also involve a variety of intermediaries that can help firms to enter into a relationship with knowledge-intensive agents (Howells, 2006). This means that learning through experience occurs with respect to specific types of agents. If the policy has been effective, the skills and knowledge gained during the project will make the funded firms more open to subsequent collaboration with these organizations. Therefore, we detail hypothesis H1 as follows.

H1a: Participation in a publicly-funded collaborative R&D project increases firms' willingness to engage in subsequent innovation-related interactions with universities or other research centres.
H1b: Participation in a publicly-funded collaborative R&D project increases firms' willingness to engage in subsequent innovation-related interactions with intermediaries.

The increase in networking activity that results from participation in a collaborative R&D project suggests that the intervention has achieved its goal. One can be content with this result, or, as in our case, one can attempt to unpack the different types of networking that can be stimulated by participating in the policy intervention. In order to do so, we propose three specific types of learning effects that firms can derive from their participation in collaborative R&D. The first is a *breadth* effect, which refers to the increase in the number of organizations with which the firm collaborates for the development of its innovation-related activity. In fact, participation in a collaborative R&D project may stimulate firms to enter into direct or indirect contact with a number of organizations with which they did not collaborate previously (Luukkonen, 2000; Fier et al., 2006; Caloffi et al., 2015). This may happen, for example, when the policy requires the formation of partnerships that include a minimum amount of partner organizations (Rossi et al., 2016). As firms that have direct or indirect ties with other organizations in existing networks are more likely to form future alliances (Gulati, 1995; Powell et al., 1996; Walker et al., 1997; Chung et al., 2000), these new partners may form the basis for an expansion of firm's network. Therefore:

H2: Participation in a publicly-funded collaborative R&D project stimulates firms to expand the breadth of their networks, i.e. to collaborate with an increased number of partners in subsequent innovation-related activities.

The second effect is the *composition* effect. This effect refers to the fact that, as a result of policy participation, firms may begin to collaborate with new types of organizations, with which they did not collaborate previously (see also Falk, 2007). This may happen, for example, when the policy requires firms to network with certain types of organization with which they had no previous relationships (Rossi et al., 2016). More generally, as participation in collaborative R&D increases firms' knowledge and skills, they may be able to work with a wider range of organizations after the end of the project. For this reason we put forward the following hypothesis:

H3: Participation in a publicly-funded collaborative R&D project stimulates firms to change the composition of their networks by collaborating with new types of partners in subsequent innovation-related activities.

The third effect is the *intensification* effect, which refers to the fact that policy participation can stimulate greater frequency of existing collaborations with external organizations (greater network depth). Given that SMEs have a relative lack of resources to be devoted to activities which fall outside their core operations, their involvement in innovation networks can be sporadic and episodic (Caloffi et al., 2015). Participation in a publicly-funded collaborative R&D project could stimulate small firms to carry out R&D activities in a more stable and structured way than previously and, for this reason, trigger - ex post - an intensification of existing collaborations. Drawing on the above, we formulate our fourth hypothesis as follows:

H4: Participation in a publicly-funded collaborative R&D project stimulates firms to increase the depth of their network, i.e. to intensify their collaborations with existing partners.

3. Tuscany's regional policy in support of R&D collaborations

Our empirical analysis focuses on a policy supporting collaborative R&D projects implemented by an Italian region, Tuscany, with European Regional Development Funds. Since the constitutional reform introduced in the 2000s, Italian regions have been responsible for most enterprise and innovation policy, and the Tuscany region has been one of the most active promoters of collaborative R&D policies in Italy (Caloffi and Mariani, 2017). In particular, we analyze a succession of nine waves launched between 2002 and 2008 under different programmes with the same goal. These programmes constitute the entire set of network policy interventions implemented by the region in the 2000-2006 EU programming period (Russo and Rossi, 2009; Bellandi and Caloffi, 2010).

The regional government launched the above-mentioned nine policy waves in order to stimulate local SMEs to develop non-transitory forms of collaboration with universities, innovation service providers, other firms, and other organizations, in order to acquire new external knowledge and carry out R&D projects.

Through the nine waves, Tuscany's regional government funded 168 projects, which were carried out in the years 2002-2008, for a total funding of € 37 million. The following Table 1 presents some basic features of the policies, according to the year in which the intervention was launched.

Table 1. Basic features of the observed framework of policies

Year in which intervention was launched	Waves	Funded projects	Participants in funded projects (total)	Participants in funded projects (firms only)	Of which: receiving a single grant
2002	RPIA, SPD 1.7.1, SPD 1.7.2	23	363	187	135
2004	SPD 1.7.1 (A), SPD 1.7.1	20	112	48	22
2005	SPD 1.7.1	36	833	341	217
2006	RPIA	12	80	57	34
2007	SPD 1.7.1	41	333	136	70
2008	SPD 1.7.1	36	282	143	57

Notes: RPIA stands for Regional Programme of Innovative Actions, while SPD stands for Single Programming Document 2000-2006, which is the policy document that specifies the use of EU funds by the region for the programming period 2000-2006. The number of participants refers to all participation instances, including participations by organizations that did not receive any funding. As multiple participations were often admitted (both in the same wave and across different waves), the total by column does not correspond to the total number of participating organizations.

The total number of SMEs that participated in collaborative R&D projects funded through the nine waves was 677. Large firms could participate, but without receiving any public funds.[1] The funded collaborative R&D projects also involved universities and research centers, and other organizations. Given that participation in multiple waves was admitted, 142 out of the 677 participating firms received funds from more than one wave. Moreover, some firms received funds from other sources (national, European Union). Therefore, for reasons that will be explained in the following section, our analysis starts with the group of 338 SMEs that were funded only once.

4. The empirical strategy

The aim of our empirical analysis was to estimate a number of average effects of the collaborative R&D policy programme on the participating SMEs. Therefore, the estimands of interest were average treatment effects on the treated (ATT). For each outcome variable of interest, the ATT writes as follows:

$$ATT = E[Y_i(1) - Y_i(0) \mid T=1],$$

[1] 18 large firms joined the networks at different times. However, as the policy targeted SMEs, our analysis focuses only on this type of firm.

where, for each firm *i*, the effect of the participation in the policy relative to a non-participation situation is defined as the difference between the firm's two potential outcomes: $Y_i(1)$, which is the observed value of the outcome variable *Y* if the firm receives the treatment (that is, if it participates in the policy), and $Y_i(0)$, which is the unobserved value of *Y* if the firm does not receive the treatment (that is, if it does not participate in the policy). The outcome variables we are interested in will be extensively discussed in the following section 5.2. Because all quantities $Y_i(0)$ are unobserved, some assumptions are required in order to point identify the ATT. We worked under the assumption of unconfoundedness (Imbens and Wooldridge, 2009), which states that, conditional on a set of relevant pre-treatment firm characteristics, treatment assignment is independent of the potential outcomes $Y_i(1)$ and $Y_i(0)$. This assumption makes it possible to reconstruct the counterfactual quantity $E[Y_i(0)]$ exploiting information from a set of untreated firms that are similar to treated ones. Under the assumption of unconfoundedness, the ATT writes as follows:

$$ATT = E[Y_i(1) - Y_i(0) \mid T=1, X=x],$$

To estimate this ATT, we adopted a propensity-score matching approach that is common in the programme evaluation literature (Imbens and Wooldridge, 2009). Given that the variables of most interest to us, which were related to the networking behaviour of participating organizations, were not available in ready-to-use general datasets, we collected information through a questionnaire.

We developed our empirical strategy in two steps, both of which involved propensity score matching techniques, although aimed at different goals. In the first step, we performed a propensity-score based matched sampling to identify a reservoir of potential controls to be interviewed (Rosenbaum and Rubin, 1985). Then, after collecting interview information, we used propensity score matching again for the purpose of estimating treatment effects.

In particular, drawing on a set of data available in public archives (the ASIA database) for all the regional firms, in the first step we estimated a propensity score from a number of basic features such as: firms' sector, legal ownership form, province, number of employees. The matched sampling was performed year by year, by considering the SMEs involved in one policy wave at a time. In this way, we chose 5 potential controls for each treated firm. Among the controls, we also considered 391 firms that applied to the programme, but were not selected for funding.

Treated and potential controls were then invited to fill in a questionnaire to investigate their innovation behaviour before and after their participation in the policy: one year prior to the beginning of the funded project and three years after its beginning (i.e. two years after the end of the project, given that the average project length was one year). The questionnaire was sent to 2,497 firms, which responded between December 2014 and July 2015. Treated firms and potential controls were sent a link by email to access the online questionnaire, which was valid for two weeks. Subsequently, firms that had not answered were sent a reminder, with a new link. Finally, companies that had not filled out the questionnaire, or filled it only partially, were contacted by phone by the interviewers, who gathered the required information during the call. The interviews were directed to the entrepreneur or to a manager who had been involved in the funded collaborative R&D projects (for treated firms) or was responsible for R&D activities (for controls). The response rate was about 20% (489 firms). We explain below how we dealt with the problem of non-response, while more information on the questionnaire can be found in the next section.

After excluding firms that benefited from (other) government incentives in the period under observation[2], we had 79 treated firms and 364 firms among which we could choose the controls to be included in the estimation.

A critical issue in the analysis of survey data concerns the presence of missing data due to non-response, which may lead to biased estimates, especially when the lack of response depends on the outcome variable (Little and Rubin, 2014). We considered this circumstance very unlikely to occur, since we believed that the information collected through the questionnaire was not so sensitive that it would induce companies not to respond. In these circumstances, it makes sense to assume that non-response occurs at random conditional on a vector of observable variables available for all firms (sector, province, legal ownership form, number of employees), and to implement an inverse probability weighting strategy (Wooldridge, 2002; Rotnitzky, 2009). For each agent that was included in the survey, we calculated a weight equal to the inverse of its probability of response and then used it in the stage of estimation of the ATT. More precisely, the probability of response $\pi_{i,T=1}$, with T=1 identifying the treated firms, is estimated by using a logistic model. The inverse-probability weight $w_{i,T=1}$ is given by $1/\pi_{i,\,T=1}$.

As a second step of our analysis, we improved the matching between treated and controls by calculating a new propensity score that included the information collected through the survey. We were thus able to identify a number of treated-control matches not only on the basis of the firms' structural features as described above, but also on the basis of the number and type of relationships with universities, innovation services providers and other manufacturing enterprises that these SMEs had before the policy. Moreover, we considered the type of innovative behaviours that the

[2] This choice was justified by the fact that in the case of multi-treated firms it is difficult to identify a clear causal link between participation in a specific programme and firms' outcomes. This is the same reason for which, as mentioned in section 3, we also excluded firms that had benefited from more than one treatment within the programmes observed, which were not invited to take part in the survey.

SMEs had before the policy, and in particular whether they had some absorptive capacity or whether they were innovators (i.e. they introduced innovative products and services on the market). The matching was made through the nearest neighbor method, with replacement, using the previous propensity score as a distance measure. We imposed an exact match for treatment year and lagged value of the outcome variable.[3] The ATT estimation was done by applying the inverse-probability weights illustrated above to each pair of treated-control units. Finally, standard errors were obtained using the analytic asymptotic variance estimator by Abadie and Imbens (2006), which is appropriate when matching occurs with replacement and with a fixed number of matches.

5. Data and variables

5.1. Pre-matching and matching variables

As explained in the previous section, the data that we used in the different stages of our empirical strategy (matched sampling, calculation of the propensity score and matching) came from both administrative sources and from the survey that we performed on treated firms and potential controls. The variables are listed in Table 2, with the specification of the stage in which they were used.

SMEs were asked to provide information about the presence and the features of their innovation-related collaborations with three types of partners: i) universities and research centers; ii) innovation services providers; iii) other manufacturing enterprises. Besides checking for the presence or absence of these relationships in the two time periods before and after the end of the collaborative R&D project, we also inquired about the intensity of those relationships, and the stability of links with the same partners over time. In addition, we asked about the firm's general innovation activities, including the number of innovations realized, the amount of R&D expenditure, the presence of an internal R&D lab, and others.

In particular, in addition to information from the above-mentioned ASIA public archive, and the dummy variable related to the treatment, we included the following variables from the survey in the calculation of the new propensity score: i) a dummy variable equal to one if, before the policy, the firm had had relationships with universities or research centers (*universities pre*); ii) the same dummy variable as in i), but referred to public service providers such as innovation or technology transfer centers, which are an important type of innovation intermediary (Howells, 2006) (*intermediaries pre*); iii) the same dummy variable as in i), but referred to other firms (*other firms pre*); iv) a dummy variable equal to one if, before the policy, the firm had some absorptive capacity,

[3] We considered only firms in the common support, i.e. in the range of values of the propensity score in which we had both treated and control firms.

i.e. if the firm performed R&D and/or staff training activities (*absorptive pre*); v) a dummy variable equal to one if, before the policy, the firm had introduced new or significantly improved goods and services in the market (*innovator pre*).

The proxy for a firm's absorptive capacity was, unlike in most studies, a combination of firm's internal R&D and staff training activities. As noted by Muscio (2007), in the case of SMEs, which perform relatively little internal R&D activities, the latter processes gain particular importance.

5.2 Outcome variables

Consistently with our hypotheses, we used a number of variables to characterize different types of network effect. Because changing behaviour takes time, all the outcome variables that we considered referred to a non-immediate time horizon, which was three years after the year *t* in which the wave was launched or, because the funded projects lasted one year on average, two years after the end of the wave. First, in order to determine whether the participation in funded projects increased SMEs' willingness to engage in subsequent innovation-related interactions with external organizations, we created the variable *network persistence*, which is a dummy equal to one if the firm collaborated with external organizations after the policy. In order to detail the type of organizations with which such collaboration occurred (hypotheses H1a and H1b), we defined the following variables: i) a dummy variable equal to one if, after the policy, the firm had relationships with universities or research centers (*universities*); ii) the same dummy variable as in i), but referred to public service providers (*intermediaries*); the same dummy variable as in i) but referred to other firms (*other firms*).

Second, we analyzed different types of network effects. In order to test hypotheses H2 - H4 we defined the following three variables: *network breadth*, which is a dummy equal to one if, after the policy, the SME increased the number of organizations with which it collaborated in innovation-related activities; *network composition*, which is a dummy equal to one if, after the policy, the SME started to collaborate with at least one new type of organization with which it did not collaborate previously[4]; *network depth*, which is a dummy equal to one if, after the policy, the frequency of the relationships with existing partners increased compared to the period before the policy. These different types of network effects were tested on the subgroup of SMEs that prior to the policy collaborated with external partners in the development of their innovation activities.[5]

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[4] We considered three different types of organisation: universities or research centres, innovation intermediaries, and manufacturing firms. The variable 'collaboration breadth' took value one if, for instance, in the year t+2 the observed firm collaborated with a university and in the year t-1 the firm was not collaborating with universities.

[5] To define this latter set of variables we used the information from two questions in the questionnaire which asked the respondent to state the intensity of the relationship with universities, service providers, and other firms one year before

Table 2. Descriptives

Variable	Description	Source	Phase	Mean of treated firms	Difference between treated and control firms (firms before matching)
Outcome variables:					
Network persistence	Dummy equal to 1 if the firm interacted with external organizations in order to perform its innovative activities, 2 years after the end of the policy (i.e. at time *t*+2, with *t*=year of the policy)	I	M	0.608	0.239
Universities	Dummy equal to 1 if the firm interacted with universities in order to perform its innovative activities, 2 years after the end of the policy	I	M	0.494	0.378
Intermediaries	Dummy equal to 1 if the firm interacted with innovation intermediaries (public service providers) in order to perform its innovative activities, 2 years after the end of the policy	I	M	0.380	0.234
Other firms	Dummy equal to 1 if the firm interacted with other firms in order to perform its innovative activities, 2 years after the end of the policy	I	M	0.418	0.235
Network breadth	Dummy equal to 1 if, 2 years after the end of the policy, the firm increased its network of external collaborations	I	M	0.430	0.274
Network composition	Dummy equal to 1 if, 2 years after the end of the policy, the firm collaborated with a type of agent with which it had no previous collaborations	I	M	0.253	-0.495
Network depth	Dummy equal to 1 if, 2 years after the policy, the frequency of the relationships with existing partners had increased	I	M	0.354	0.222
Other variables:					
Collaboration pre	Dummy equal to 1 if the firm had relationships with external organizations, 1 year before the beginning of the policy (i.e. at time *t*-1, with *t*=year of the policy).	I	M	0.595	0.209
Universities pre	Dummy equal to 1 if the firm had relationships with universities, 1 year before the beginning of the policy	I	M	0.392	0.203
Intermediaries pre	Dummy equal to 1 if the firm had relationships with innovation intermediaries (public service providers), 1 year before the beginning of the policy	I	M	0.367	0160
Other firms pre	Dummy equal to 1 if the firm had relationships with other firms, 1 year before the beginning of the policy	I	M	0.392	0.114
Absorptive capacity pre	Dummy equal to 1 if the firm was an R&D performer and/or had internal training activities, 1 year before the beginning of the policy	I	M	0.620	0.204
Innovator pre	Dummy equal to 1 if the firm was an innovator, introducing products in the market, 1 year before the beginning of the policy	I	M	0.354	0.144

the participation in the funded projects and two years after the end of the project, both measured on a scale from 0=no relationship to 4=very often. The dummy took the value of one if the intensity of collaborations increased at least with respect to one type of organization (i.e. universities/intermediaries/other firms). This is the information that suffers the most from the interviewees' perceptions, as well as from the accuracy of their recall. However, it must be observed that we put these questions to the person who was directly involved in the innovative activities of the firm. Moreover, the observed firms were mostly of small size, where the entrepreneur was likely to be directly involved in all types of activity.

Sector	Categorical variable describing firms' sector:	A	S, W, M		
	Food products			0.063	-0.005
	Marble products			0.063	-0.011
	Textiles, clothing, shoes			0.127	-0.016
	Chemicals			0.038	0.014
	Metallurgy and metal products			0.165	0.005
	Computer systems, electrical machinery and equipment			0.101	0.017
	Motor vehicles, trailers			0.051	0.027
	Furniture			0.038	-0.037
	Electricity, gas, heat, water			0.013	-0.001
	Construction industry			0.051	0.007
	Wholesale and retail trade			0.013	-0.008
	Transportation services			0.013	-0.004
	Information technology			0.076	-0.033
	R&D services			0.038	-0.021
	Other business services			0.089	-0.016
	Other sectors			0.063	0.040
Employees	Categorical variable describing the number of employees	A	S, W, M		
	Micro-sized firm, with a number of employees 0<x<10			0.468	-0.033
	Small-sized firm (10<=x<30)			0.304	0.002
	Small-sized firm (30<=x<50)			0.114	-0.025
	Medium-sized firm (50<=x<250)			0.114	0.056
PPLC	Dummy equal to 1 if the firm is a public or private limited company	A	S, W, M	0.671	0.012
Province	Categorical variable describing firms' location (province):	A	S, W, M		
	Massa Carrara			0.089	0.028
	Lucca			0.038	0.001
	Pistoia			0.025	-0.019
	Florence			0.253	-0.025
	Livorno			0.101	0.013
	Pisa			0.089	-0.061
	Arezzo			0.025	-0.022
	Siena			0.127	-0.012
	Grosseto			0.089	0.048
	Prato			0.165	0.049

Notes: Minimum and maximum values are 0 and 1 respectively. 79 treated firms and 87 controls. Source refers to the type of source that was used to build the data: I stands for interviews and A stands for administrative archives. Phase refers to the specific stage of the empirical strategy in which the variable was used, which is specified as follows: S=matched sampling; W=weights; M=matching: estimation of network effects. Mean of treated firms reports weighted values. The difference between treated and controls was calculated using matched pairs of treated and controls after matching, and figures are absolute values. Note that both controls and treated firms can be repeated.

As can be seen from the table, the difference between treated and controls related to the covariates measured before the policies (i.e. at time t-1) was very small. The same applies to the time-invariant features of the observed firms that were used for the propensity score. Moreover, this difference is further reduced in the estimation of the ATT thanks to the imposition of an exact match for the lagged values of the outcome variables and for the year of the wave.

6. The network effects of the policy

Observation of the entire group of treated firms showed that the collaborative R&D policy generated network effects only with respect to certain types of organizations. On average, we did not find any evidence of a network persistence effect (the variable *network persistence* reported positive but not significant values), which means that the hypothesis H1 is rejected. However, when we differentiated the effect with respect to the types of agents with which firms collaborated, we found that the policies had a positive effect particularly on the relationships with universities. Thus, our hypothesis H1a is confirmed. On the contrary, we did not find any networking effect with respect to innovation intermediaries (H1b is rejected), nor to other firms.

Table 3. Behavioural effects of the policies on the whole population of treated firms

Outcome variable	ATT	SE	
Network persistence	0.142	0.092	
Universities	0.224	0.076	***
Intermediaries	0.096	0.080	
Other firms	0.087	0.082	

Note to table: 79 treated firms and 87 controls. Statistical significance: $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

The analysis of the different types of network effects enables us to account for the possibility that the policy intervention had different effects on different types of participants. In particular, we considered the following two groups of treated firms: those that prior to policy participation were accustomed to collaborating with other organizations for the development of their innovation-related activities, and those that did not have this inclination for collaboration (Table 5).

For both groups, we found that the policy generated network effects only with respect to some types of organizations (universities in particular). It is interesting to note that the network persistence effect was greater for firms that had a previous inclination towards collaboration than for non-collaborating firms. Indeed, for the former group, the probability of creating subsequent relationships with universities increased by about 27% (about +22% in the case of the relationships with other firms), while for firms that had no previous collaborations this probability only increased by +14%. Moreover, firms with a prior inclination for collaboration also enjoyed an increase in their relationships with other firms. This would confirm that networking can have a cumulative effect. No significant effects were reported in the case of the relationships with intermediaries. Probably, after having worked together with the universities and research centers on the funded projects, SMEs had learned to interact directly with these organizations, without the need for intermediaries such as innovation centers and the like.

Besides increasing the willingness to engage in subsequent innovation-related interactions with universities, participation in the policy induced changes in the composition of the partners in innovation-related relationships of firms that had prior collaborations. Indeed, the variable *network composition* increases by 23% in the group of treated firms with respect to controls, which means that hypothesis H3 is confirmed. In particular, inspection of the data shows that firms that before the policy did not have any collaboration with universities began to create links with these organizations. On the other hand, we did not observe any significant effect on the increase in the number of external partners (*network breadth*), nor on the intensification of innovation-related relationships (*network depth*), which means that hypotheses H2 and H4 are rejected.

In short, as a result of participation in the collaborative R&D policy, firms tended to keep the same number of external collaborations that they had before the policy, as well as the same intensity of such collaborations; but they introduced some significant changes in the type of partners that they had, starting to work with universities. Therefore, the effect of the policy seems to be particularly interesting. It did not stimulate collaboration in a generic sense, but it supported the matching between SMEs and knowledge-intensive organizations such as universities or research centers. Firms that had a prior inclination towards collaboration did not radically change their behaviour, but for the fact that they started to collaborate with such organizations. In conclusion, given the difficulties of SMEs in establishing relationships with universities, we can say that the observed policy achieved an important result, which was in line with the policymaker's goal.

Tab 5. Different types of network effects

Outcome variable	Firms with prior collaborations		Firms without prior collaborations	
	ATT		ATT	
Network persistence	0.114		-0.001	
	(0.103)		(0.110)	
Universities	0.271	**	0.145	*
	(0.132)		(0.085)	
Intermediaries	0.145		-0.052	
	(0.124)		(0.096)	
Other firms	0.223	*	0.005	
	(0.133)		(0.083)	
Network breadth	0.119			
	(0.117)			
Network composition	0.212	**		
	(0.083)			
Network depth	0.095			
	(0.121)			

Notes: Treated firms in the group of firms with prior relationships are 47, while controls are 33. Standard errors are in brackets. Statistical significance: $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

7. Conclusions

The analysis reported in this paper has shown that collaborative R&D policies are able to generate a persistent change in the networking behaviour of participating firms. Adopting a counterfactual approach to the evaluation of a collaborative R&D policy programme implemented in an Italian region, we found that the participation in funded collaborative R&D projects stimulated subsequent collaborations particularly with universities and research centers. We also tried to go a step further in the analysis of the various types of persistent network effects that can be generated by the policy. For those firms that were accustomed to collaborating with external organizations prior to their policy participation), we found an interesting effect. Policy participation did not induce firms to alter their collaborative behaviour (i.e. they maintained more or less the same number of external partners, as well as the intensity of their collaborations), but for the fact that they replaced some old partners with universities and research centers. A similar replacement effect has been documented by other studies showing that firms which participate in a policy programme tend to change their partners with respect to the pre-policy period (Fier et al., 2006; Caloffi et al., 2015).

Our analysis reveals that the policy has achieved some of its main goals, which were related to the policymaker's aim to encourage interorganizational relationships, particularly those that can be more generative of innovation. This is a somewhat encouraging result, given that similar policies have been implemented in many European regions to facilitate upgrading and innovation in SMEs through the development of relationships with other organizations.

However, the analysis suffers from some limitations. First, the size of our sample was quite small. This was due (i) to the small initial population of treated firms, because we were dealing with a regional policy intervention which was limited in size, and (ii) to the need to collect information using an ad-hoc questionnaire rather than publicly available secondary data. This problem is not easy to remedy. While it may be possible to identify larger populations of treated firms by focusing on national-level policy programmes (see e.g. Vanino et al., 2017), information about firms' networking behaviour remains difficult to collect from public sources. Therefore it is likely that questionnaires need to continue to figure prominently in studies of network effects, particularly if different types of network effects are considered.

Second, since we intended to conduct an in-depth exploration of network effects, we did not consider other types of effects that can be generated by policy participation, and we did not explore whether or not the main goal of the policy – namely, that of promoting R&D – was achieved.

Indeed, we are aware that we are analyzing only a part of the story. As discussed by Veugelers (1997), studying network effects *per se* is not enough. More longitudinal research would be needed to determine the relationships (if any) among the various types of effects generated by the policy, and in particular on the mediating role of the firm's network on the production of different types of effects.

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