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A tale of persistent network additionality, with evidence from a regional policy

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A tale of persistent network additionality, with evidence from a regional policy

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Abstract

Adopting a counterfactual approach to the evaluation of a regional R&D collaboration policy, carried out in Tuscany (Italy), we investigate different types of persistent network additionality, namely persistence effect, breadth effect, composition effect, and depth effect. Our findings reveal that this R&D collaboration policy has been able to generate some persistent changes in the networking behaviour of participating firms, particularly fostering their collaboration with universities. Network additionality has been greater for firms that were previously accustomed to collaborating with other firms, than for less collaborative firms. With respect to the former firms, we also find a composition effect, which implies a change in their type of partners in innovation-related activities. We find, instead, no evidence of network breadth and network depth effects.

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

JEL code: O38, O32, D04,

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1. Introduction

The last twenty years have witnessed the diffusion of innovation policies that attempt to foster innovation by encouraging interactions between 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 promoting R&D is the primary objective of such interventions, the instrumental objective is clearly that of stimulating networking. Many regional interventions of this kind have targeted small and medium-sized firms (SMEs), which, despite their pressing need for sourcing external knowledge, have limited knowledge and skills to invest in the screening and identification of partners to collaborate with (Davenport et al., 1998; Bougrain and Haudeville, 2002; Narula, 2004).

The problem of how to analyze and evaluate such policies has entered the agenda of both researchers and policymakers. The concept of network or collaboration additionality, which refers to the ability of a policy intervention to stimulate learning processes that result in changes in the network of participating organisations 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), can be fruitfully used for this purpose. Indeed, it is important to investigate whether and to what extent R&D collaboration policies have achieved one of their main goals, that is, to support participating firms' ability to collaborate with other organisations.

Existing assessments of R&D collaboration policies have focused on the *simultaneous* network additionality of the interventions, measured throughout the duration of the collaboration projects. Studies have analyzed whether these policies have fostered R&D collaborations between firms that were not previously engaged in these activities (e.g. Afcha Chavéz, 2010; Wanzenböck et al., 2012); other studies, focusing on firms that were already used to collaborate with other organisations, have examined whether these policies have induced them to collaborate with new partners (Davenport et al., 1998; Luukkonen, 2000; Caloffi et al., 2015). However, evidence on the *persistent* network additionality of R&D collaboration policies, beyond the duration of the collaboration projects, is still scant. The seminal contribution of Fier et al. (2006), which shows that university-industry R&D collaborations that start with policy support are likely to end with the end of the policy, is, to our knowledge, the only one to have taken a step in this direction.

The aim of the paper is to fill this gap by exploring empirically the persistent network additionality of R&D collaboration policies. We also add to the existing literature by untangling different types of network additionality that can be stimulated by policy participation *after* the end of the funded project, which we test empirically: i) a persistence effect, which occurs when firms continue to collaborate with external organisations; ii) a breadth effect, which refers to an increase in the breadth of firms' networks (firms create relationships with organisations with which they did not have any prior connections); iii) a composition effect, which occurs when firms change the type of organisations with which they collaborate; and, iv) a network depth effect, which refers to a change in the intensity of collaborations.

While previous evidence on network additionality has been mainly descriptive, we use a propensity score matching approach (Rosenbaum and Rubin, 1983) to make inference 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 an R&D collaboration policy intervention can induce firms to learn more about networking, and what are the likely consequences for their subsequent propensity to network with other organisations. Section 3 illustrates the empirical case, which provides the data we have used to test our hypotheses: a regional R&D collaboration policy implemented in the Italian region of Tuscany between 2002 and 2008 with European Regional Development Fund (ERDF) support. Section 4 explains the empirical strategy we have 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. R&D collaboration policies and their persistent network effects

To build a logical causal chain that can guide us in the empirical analysis of the persistent network additionality of R&D collaborations, we draw on recent contributions on the learning capabilities of organisations (Clarysse et al., 2009; Knockaert et al., 2014; Roper and Dundas, 2016; Chapman and Hewitt-Dundas, 2016), which reference the concepts of organisational learning by experience (Cyert and March, 1963), interaction with external organisations (Huber, 1991; Levinson and Asahi, 1996; Kogut, 2000) and absorptive capacity (Cohen and Levinthal, 1998, 1990). 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 networks, firms must possess a range of knowledge and capabilities to value, interpret and absorb information and knowledge that flows from other organisations (Cohen and Levinthal, 1989, 1990). Policy can play an important role in this process. Indeed, by funding R&D collaboration projects, policymakers encourage firms to undertake two types of activities that can influence firms' networking abilities: engagement in R&D, and networking.

Through networking, firms' personnel can learn how to manage inter-organisational relationships through experience and interaction (Cyert and March, 1963; Huber, 1991; Kogut, 2000). In the course of R&D collaboration projects, firms' managers may create or strengthen the appropriate interfaces and routines to exchange information and knowledge with other organisations, and other staff can learn how to use and modify them (Van den Bosch et al., 1999; Tierlinck and Spithoven, 2013).

Through engagement in 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 to enter into future collaborations (Powell *et al*., 1996; Lane and Lubatkin, 1998; Lane *et al*., 2006; Escribano et al., 2009; Huang and Yu, 2011).

Since firms' learning depends on the knowledge they already possess and on the routines that are in place (Cohen and Levinthal, 1989, 1990; Van den Bosch *et al*.

1999), the new organisational structure and the new knowledge and competencies that are sourced through interactions with other organisations can improve firms' ability to interact and to learn from interactions, thus increasing the likelihood that they will enter into further relationships once the R&D collaboration project has been completed. Therefore, drawing on the above, we put forward our hypothesis H1.

H1 (persistence effect): Participation in a publicly-funded R&D collaboration project increases SMEs' willingness to engage in subsequent innovation-related interactions with external organisations.

R&D collaboration policies do not usually aim just to stimulate networking in general terms. Very often, these policies aim to facilitate technology transfer processes and to stimulate networking with specific types of organisations – in particular, with knowledge-intensive organisations such as universities or other research centers (Cunningham and Gök, 2016), as well as with a variety of intermediaries that can support SMEs' engagement with knowledge-intensive agents (Howells, 2006). This means that learning through experience occurs with respect to some types of agents. If the policy has been effective, the skills and knowledge gained during the project will render the firms that have been involved in R&D collaboration projects more open to subsequent collaboration with these organisations. Therefore, we detail hypothesis H1 as follows.

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

The increase in networking that results from participation in an R&D collaboration policy tells us that the intervention has achieved its goal. One can be content with this result, or can, as in our case, attempt to unfold the different types of network additionality that can be stimulated by participation in the policy intervention. In order to do so, we consider three specific types of learning effects that firms can derive from their participation in publicly-funded R&D collaboration projects. The first is a *breadth* effect, which refers to the increase in the number of organisations with which the firm collaborates for the development of its innovation-related activity. In fact, participation in the R&D collaboration projects may stimulate firms to enter into direct or indirect contact with a number of organisations 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 organisations (Rossi et al., 2016). As firms that have direct or indirect ties with other organisations 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 a broadening of the firm's network. Therefore:

H2 (breadth effect): Participation in a publicly-funded R&D collaboration project stimulates SMEs to expand the breadth of their network, 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 organisations, with which they did not collaborate previously (see also Falk, 2007). This may happen, for example, when the policy requires the creation of partnerships that include a certain type of organisation with which the company had no previous relationships (Rossi et al., 2016). More generally, as participation in the R&D project increases the firm's knowledge and skills, after the end of the funded project the firm may be able to work with a wider range of organisations. For this reason we put forward the following hypothesis:

H3 (composition effect): Participation in a publicly-funded R&D collaboration project stimulates SMEs to change the composition of their network by collaborating with new types of partners in subsequent innovation-related activities.

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

H4 (depth effect): Participation in a publicly-funded R&D collaboration project stimulates SMEs to intensify the collaboration with existing partners

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

Our empirical analysis focuses on a policy supporting R&D collaboration projects implemented by the Tuscany region, in Italy, with ERDF support. Since the constitutional reform introduced in the 2000s, Italian regions are responsible for most enterprise and innovation policies, and Tuscany has been one of the most active promoters of R&D collaboration policies in Italy (Caloffi and Mariani, 2017). In particular, we analyze nine public tenders that were launched between 2002 and 2008 under different programmes, all having the same goal. These constituted the whole 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 public tenders in order to stimulate local SMEs to develop non-transitory forms of collaboration with universities, innovation service providers, other firms, and other organisations, in order to acquire new external knowledge and carry out R&D projects. Through these tenders, Tuscany's regional government funded 168 projects, for a total funding of € 37 million, which were carried out in the years 2002-2008. The following Table 1 presents a count of the organisations that participated in these tenders, grouped according to the year in which the tenders were launched.

Table 1. Basic features of the observed framework of policies

Year in which tender was launched	Acronym of the policy programme	Number of funded R&D collaboration projects	Number of participants in funded R&D collaboration projects	Of which: number of firms in funded R&D collaboration projects	Of which: number of firms in funded R&D collaboration projects 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

Note to table: RPIA stands for Regional Program 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 organisations that did not receive any funds. As multiple participation was often admitted (both in the same tender and across different tenders), the total by column does not correspond to the total number of participating organisations.

A total of 677 SMEs were involved in the observed tenders. Large firms could participate, but without receiving any public funds. Besides firms, the R&D collaboration projects involved universities and research centers, and other organisations. Given that participation to multiple tenders was admitted, 142 out of the 677 participating SMEs received funds from more than one tender. For reasons that will be explained in the following section, our analysis focuses on the group of 535 SMEs that only received a single grant.

4. The empirical strategy

In order to evaluate the effects of the observed policy, we adopt a matching approach that is common in the programme evaluation literature (Imbens and Wooldridge, 2009), and in particular we follow the procedure systematized by Abadie and Imbens (2011).[1] Given that the variables we are most interested in, which are related to the networking behaviour of participating organisations, were not available in ready-to-use general datasets, we collected information through a questionnaire.

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[1] However, unlike these authors we do not use a double robust correction because we have binary variables.

We developed our empirical strategy in two steps, both of which rely on propensity score matching techniques, although aimed at different goals. In the first step, we performed a matched sampling to identify a reservoir of potential control firms to be interviewed. The control firms are SMEs that did not receive funding under any of the nine tenders, but which shared many other characteristics with the 535 SMEs that participated in the nine tenders and received a single grant (the latter are called the 'treated firms', following the standard terminology in matching models). Then, in the second step, after having collected interview information, propensity score matching was used again for the purpose of estimating the effects of the policy on the SMEs' networking behaviour ('treatment effects').

In particular, drawing on data available in public archives (the ASIA public archive)[2] 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 tender at a time. This way, we chose 5 potential control firms for each treated firm, with replacement. Among the control firms, we also considered the 391 firms that participated only in the 130 projects that unsuccessfully applied for funding under the nine tenders ('non-funded' firms).

We necessarily restricted our analysis to the treated firms that survived throughout the whole period under analysis (85%). Treated and potential controls, the latter including non-funded firms, were then invited to fill in a questionnaire to investigate their innovation behaviour before and after their participation in the policy in year *t*: one year prior to the beginning of the publicly-funded R&D collaboration project (*t-1*) and three years after the beginning of the project (i.e., two years after the end of the project, given that the average project length was one year; *t+2*). The questionnaire was sent to 2,497 firms, which answered between December 2014 and July 2015. 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.

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[2] ASIA is a database collected and maintained by Italy's national statistical agency ISTAT. ASIA in particular collects a wide range of economic information about all Italian companies.

We asked firms whether they had benefited from (other) government incentives in the period under observation, in order to exclude multi-treated firms. For this reason, we excluded 46 respondents.[3] Of the remaining 443 respondents, 79 were treated firms and 364 were 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 as being very unlikely to occur, since we believed that the information collected through the questionnaire was not so sensitive as to push companies to not respond. On the other hand, we worried that the answer might still not be regarded as completely random. Under these circumstances, it makes sense to assume that no response occurs at random conditional on a vector of observable variables, including those used for estimating the propensity score. Therefore, in order to deal with this problem, we implemented 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 average treatment on the treated (ATT). In so doing, the contribution of each respondent is directly proportional to the "rarity" of information provided by the same respondent. In order to estimate the probability of response we used the variables that had been already used to perform the matched sampling (sector, province, legal ownership form, number of employees at time t-1). More precisely, the probability of response $\pi_{i,T=1}$, with T=1 identifying the treated firms, is estimated by means of a logistic model, whose response variable equals one if the treated firm participates in the survey and zero otherwise. The inverse-probability weight $w_{i,T=1}$ is given by $1/\pi_{i,T=1}$.

[3] This choice is 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 tender 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 tender observed, which were not invited to take part in the survey.

The second step of our analysis consisted in improving 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 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 the SMEs had before the policy, and in particular whether they had some absorptive capacity or whether they were innovators (i.e. whether they had introduced innovative products and services on the market).

Having calculated the new propensity score, the matching was then made through the nearest neighbor method (Becker and Ichino, 2002; Caliendo and Kopeinig, 2008). Each treated firm was matched with the nearest control, and we imposed an exact match for treatment year and lagged value of the outcome variable.[4] Finally, the ATT estimation was done as follows. First, we applied the inverse-probability weights illustrated above to the treated units. Each control unit received the weight of the treated firm to which it was matched. This weighting approach makes sense if one is interested in an ATT, where control firms are supposed to be the twins of treated firms. Second, for each of the outcome variables, we computed the ATT as the difference in means between treated firms and the corresponding (weighted) controls: a positive and significant value of the ATT would indicate that the policy intervention had an effect the corresponding outcome variable, since the treated firms after the policy intervention had values of the outcome variables that were higher than those of matching control firms that had not benefitted from the policy intervention.

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

5. Data and variables

5.1. Pre-matching and matching variables

As explained in the previous section, the data we used in the different stages of our empirical strategy (matched sampling, calculation of the propensity score and matching) came both from administrative sources and from the survey 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.

The survey was performed from December 2014 to 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 another reminder, with a new link. Finally, companies that had not filled out the questionnaire, or that had filled it only partially, were contacted telephonically and asked to fill in the questionnaire during the call. The interviews were directed to the firm's CEO or to a manager who had been involved in the R&D collaboration projects (for treated firms) or was responsible for R&D activities (for controls).

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, and iii) other manufacturing enterprises. Besides checking for the presence or absence of these relationships in the periods before and after the end of the R&D collaboration project, we also asked information about the intensity of those relationships, and the stability of links with the same partners over time. In addition, we posed questions about the firm's general innovation activities, including the number of innovations created, the amount of R&D expenditure, the presence of an internal R&D lab.

In addition to information from the ASIA public archive and the dummy variable related to the treatment, in the calculation of the new propensity score we included the following variables from the survey: i) a dummy variable taking the value of one if, before the policy, the firm 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 taking the value of one if, before the policy, the firm had some absorptive capacity, i.e. if the firm performed R&D and/or staff training activities (*absorptive pre*); v) a dummy variable taking the value of 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 is, unlike most studies, a combination of the 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 relevance.

5.2 Outcome variables

Consistently with the hypotheses that we have presented above, we use a number of variables to characterize different types of network additionality. As changing one's behaviour takes time, all the outcome variables we consider refer to a non-immediate time horizon, which is three years after the start of the project or, as the R&D collaboration projects lasted one year on average, two years after the end of the project (*t+2*). First, in order to understand whether the participation in these projects increased SMEs' willingness to engage in subsequent innovation-related interactions with external organisations, we created the variable *network persistence*, which is a dummy with value one if the firm claimed to collaborate with external organisations after the policy. In order to detail the type of organisations with which such collaboration occurred (see hypotheses H1a and H1b), we defined the following variables: i) a dummy variable with value 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*).

Table 2. Descriptives

Variable	Description	Source	Phase	Mean of treated firms	Difference between treated and control firms (firms after matching)
Outcome variables:					
Network persistence	Dummy with value 1 if the firm had relationships with external organisations in order to perform its innovative activities, 2 years after the end of the policy (i.e. from time *t*+2 to time *t*+3, with *t*=year of the policy)	I	M	0.608	0.239
Universities	Dummy with value 1 if the firm had relationships 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 with value 1 if the firm had relationships 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 with value 1 if the firm had relationships 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 with value 1 if, 2 years after the end of the policy, the firm had increased its network of external collaborations	I	M	0.430	0.274
Network composition	Dummy with value 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 with value 1 if, 2years after the policy, the frequency of the relationships with existing partners, with which collaboration in t-1 was infrequent, increased	I	M	0.354	0.222
Other variables:					
Collaboration pre	Dummy with value 1 if the firm had relationships with external organisations, 1 year before the beginning of the policy (i.e. time *t*-1, with *t*=year of the policy).	I	M	0.595	0.209
Universities pre	Dummy with value 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 with value 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 with value 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 with value 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 with value 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
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
Joint_stock	Dummy taking the value of 1 if the firm is a joint-stock 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

Note to table: Minimum and maximum values are 0 and 1 respectively. Treated firms are 79 and control firms are 87. Source refers to the type of source that we 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 we have used the variable, which is specified as follows: S=matched sampling; W=weights; M=matching: estimation of network additionality. Mean of treated firms reports weighted values. The difference between treated and controls is 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.

Second, we analyzed different types of network additionality of the policy. In order to test hypotheses H2 - H4 we defined the following three variables: *network breadth*, which is a dummy with value one if, after the policy, the SME increased the number of organisations with which it collaborated in innovation-related activities; *network composition*, which is a dummy with value one if, after the policy, the SME started to collaborate with at least one new type of organisation with which it did not collaborate previously[5]; *network depth*, which is a dummy with value one if, after the policy, the frequency of the relationships with existing partners, with whom collaboration was occasional, increased compared to the period before the policy. These different types of network additionality are tested on the two subgroups of SMEs that, prior to the policy, did and did not collaborate with external partners in the development of their innovation activities.[6]

As can be seen from Table 2, the difference between treated and control firms related to the covariates measured before the policies (i.e. at time *t-1*) is very small. The same holds true for the time-invariant features of the observed firms that we have inserted in the propensity score. It has to be also noted that this difference is further reduced in the estimation of the ATT thanks to the further imposition of an exact match for the lagged values of the outcome variables and for the year of the tender.

6. The network effect of the policy

The observation of the entire group of treated firms shows that the R&D collaboration policy has generated network additionality only with respect to certain types of organisations. On average, we do not find any evidence of persistence effect (the variable *network persistence* reports 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 could collaborate, we find that the policies had a positive effect particularly on the relationships with universities. Thus,

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[5] We considered three different types of organisations: universities or research centres, innovation intermediaries and manufacturing firms. The variable *network composition* takes the value of 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.

[6] To define this latter set of variables we used the information from two questions of the questionnaire, which asked the firm's CEO (or the manager responsible for the firm's R&D activities) what was the intensity of the relationship with universities, service providers, and other firms one year before the participation in the funded project and two years after the end of the project, both measured in a scale from 0=no relationship to 4=very often. The dummy takes the value of one if the intensity of the collaboration increased at least with respect to one type of organisation (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 memories. However, it must be observed that these questions were asked to the people who were directly involved in the innovative activities of the firm. Moreover, the observed firms were mostly of small size, and the respondents were directly involved in all types of activities.

our hypothesis H1a is confirmed. On the contrary, we do 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: Treated firms are 79 and controls are 87. Statistical significance: $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

The analysis of the different types of network additionality we described above lets us account also for possible effects of the policy intervention on the type and intensity of the participating firms' collaborations. We considered the following two groups of treated firms: those that prior to policy participation were accustomed to collaborate with other organisations for the development of their innovation-related activities, and those that did not have this kind of collaboration experience (Table 4).

For both groups, we found that the policy generated network additionality only with respect to some types of organisations (universities in particular). It is interesting to note that network persistence was greater for firms that had previous experience of collaboration than for less collaborative 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 prior propensity towards 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, companies had learned to interact directly with these organisations, 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. An inspection of the data shows that firms that before the policy did not have any collaboration with universities began to create links with these organisations. 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 policy participation, firms tended to keep the same number of external collaborations they had before the policy, as well as the same intensity of such collaborations, but they introduced some relevant changes in the nature of their partners, 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 organisations such as universities or research centers. Firms that had a prior propensity towards collaboration did not radically change their behaviour, but for the fact that they started to collaborate with such organisations. In conclusion, given the difficulties for SMEs to establish relationships with universities, we can say that the observed policy has achieved at least one important result, that to stimulate relationships between SMEs and universities, which is in line with the policymaker's goal.

Table 4. Different types of network additionality

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)			

Note to table: 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

Our paper shows that R&D collaboration policies are able to generate some persistent changes in the networking behaviour of participating firms. Adopting a counterfactual approach to the evaluation of an R&D collaboration policy intervention implemented in an Italian region, we have found that the participation to publicly-funded R&D collaboration projects stimulated subsequent SMEs' collaborations particularly with universities and research centres.

This paper tries to go a step further into the analysis of the various types of persistent network additionality that can be generated by R&D collaboration policy. For those firms that had a prior propensity to collaborate with external organisations (prior to their policy participation), we find 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 they replaced some old partners with universities and research centers. A similar replacement effect has been documented by other studies that show how firms that enter into the policy 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 achieved at least some of its main goals, which were related to the policymaker's willingness to encourage inter-organisational relationships, particularly those that can be more generative of innovation. We have decided to stop here, without considering other types of additionality effects that can be generated by policy participation, and without exploring whether the main goal of the policy – namely, that of promoting R&D – was achieved or not. Our decision was motivated by the willingness to conduct an in-depth exploration of network additionality. However, we are well aware of the fact that we are analysing only a part of the story. As discussed by Veugelers (1997), the network per se is not enough. More longitudinal research would be needed to investigate what are (if any) the relationships between the various types of additionality generated by the policy (including R&D additionality) and in particular the mediating role of the network.

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