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How can R&D programs induce unplanned R&D collaborative networks in clusters?

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Abstract: R&D policies are usually designed to enhance firms' internal capabilities, but do not explicitly target R&D cooperation. In this research, we propose that R&D programs can be a suitable instrument when it comes to fostering informal collaborative networking. We focus on a regional level, the cluster, and establish that firms can use their R&D subsidies not only to become more innovative, i. e. input-output additionality, but also to develop R&D informal collaborations, i. e. behavior additionality. To test this hypothesis, relational data from a biotechnological cluster in Alicante (Spain) have been analyzed. Results from ERGM confirm that promoting internal R&D efforts prompts the formation of knowledge-based relationships at the cluster level. Policy makers should consider this unforeseen behavior when designing and evaluating non-collaborative R&D support programs. New evidence on the role of distant and diverse non-local linkages on local network dynamics is also provided.

Keywords: Industrial cluster, Innovation policy, Exponential Random Graph Model, Behavioral additionality, Informal Networks

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1 Introduction

The need to innovate remains crucial in the minds of policy makers. Particularly in countries with multi-level policy frameworks (Blanes and Busom 2004), the increasing presence of regional governments in the innovation policy arena raises their interest in whether public incentives affect firms' performance. Policy makers multiply tailored programs according to the micro-level conditions of their contexts, making regional innovation policy a constitutive element of the regional innovation system (Edquist 2011). Within these programs, stimuli seek to gloss over firms' under-investments in innovation, consequence of the imperfect appropriability of the knowledge produced (Falk 2007) or the endemic cost of the acquisition of external knowledge (Gök and Edler 2012). Policy makers typically employ R&D to increase investments in firms' resources and capabilities, but not to induce cooperation explicitly.

In this context, the relevance of the "local" has brought regions into the focus of innovation policy (Cooke *et al.* 1997) rooted in the relevance that knowledge locally created and shared between co-located agents has on innovation. Economic geographers have highlighted that location does indeed matter for knowledge creation, interactive learning and innovation (Bathelt *et al.* 2004). Despite spatial propinquity just explaining part of the story (Giuliani 2013, Balland *et al.* 2016), colocation of firms with other actors with related yet complementary and diverse knowledge and capabilities leads to a valuable local buzz and higher innovation (Bathelt *et al.* 2004).[1] Locations inside clusters facilitate knowledge sharing, thanks to frequent interactions and an atmosphere of trust, as has been broadly tested in explaining geographical clustering and innovation (Markusen 2003).

As a consequence, regional policy makers would not only be interested in the direct positive effect that subsidies may imply in terms of higher innovation capacity for the recipient of the subsidy, but also in the indirect effect that it may have in promoting local knowledge diffusion. That is, when evaluating subsidies, regional governments should consider both the direct benefits that the firm receiving the subsidies has in terms of higher R&D efforts or innovative results -i. e. input-output additionality-, but also the indirect effect related to the impact on networking. While the R&D subsidies are designed to foster direct inno-

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1 In this research we consider cluster as a geographic concentration of interconnected firms in a particular sector. As long as these co-located firms also develop a strong structural cohesion they will develop R&D collaborations, as we measure in this research.

vation effects, indirect effects within a cluster – related to fostering collaboration inside the local network – also need to be considered. The unplanned effect of non-collaborative R&D policies on collaboration is the focus of this research.

Innovation policy effects have mostly been viewed in the form of input-output additionality (Roper *et al.* 2008, Hottenrott and Lopes-Bento 2014), as well as in terms of their impacts on cluster formation (Nishimura and Okamuro 2011, Martin *et al.* 2011). That is, along with evaluating input and output outcomes, it is necessary to assess the impact of innovation policies on a firm's associational behavior (Clarysse *et al.* 2009) in terms of collaborative R&D networks. This behavioral additionality is an expected outcome in regional policies where the key aim is to address network failure, particularly within the field of innovation (Gök and Edler 2012, Vicente 2014).

Considering this, the objective of this research is to assess how R&D-type innovation programs that target processes within firms are also inadvertently fostering mutuality-based innovation, i. e., the effect that non-collaborative R&D programs targeting firms' internal technologies have on firms' informal collaborative behavior, and therefore on the emergence of organic, interactive learning-based forms of innovation.

In doing so, we follow pioneering research that evaluates the effect of R&D programs on collaborative network behavior inside clusters (Nishimura and Okamuro 2011, Caloffi *et al.* 2018). In particular, we try to contribute by applying advanced Social Network Analysis (SNA) to the evaluation of innovation policies. Given the emphasis on knowledge flows inherent to collaborative innovation models, SNA "per se" or combined with other techniques will help to better perceive how firms adapt their networks as a function of the characteristics R&D support. Along with recent methodological (Giuliani and Pietrobelli 2016) and empirical contributions (Cantner et al. 2013, Vonortas 2013), this paper applies stochastic models for informal network dynamics to determine whether a firm's participation in a non-collaborative R&D regional program relates to the formation of informal inter-firm linkages, while controlling for a set of structural and covariate effects that may influence network formation (Giuliani and Pietrobelli 2016).

Secondly, we aim to enrich the emerging research on the dynamics of networks in clusters (Molina-Morales *et al.*, 2015, Lazzeretti and Capone 2016, Balland *et al.* 2016, Giuliani *et al.* 2018, Juhász 2021). Abundant research has evaluated the reinforcing role that internal R&D has on developing a local network (Spithoven and Teirlinck 2015). Nevertheless, whether R&D supported by direct subsidies would have the same effect, depends on the extent to which the intended creation of new organizational routines and capabilities inside the firm will also have the unintended effect of facilitating informal collective learning processes based on tacit knowledge-sharing.

Finally, we develop this research with the backdrop of the Valencian regional government's approach with regard to innovation programs and the growing relevance of the biotech industry in the economic fabric of this region. This site fits in well with our aims since the biotech cluster is well-established and the industry represents a major target of regional innovation policy initiatives. Information from the Research and Technological Development Program (RTDP henceforth), which represents the core of the regional R&D policy, facilitated the identification of cluster firms that secured subsidies and received non-collaborative R&D support.

The remainder of the article is organized as follows. In the next section, we present the basic theoretical rationales and our proposition. In section 3, the cluster and the policy programs analyzed are described. Furthermore, the research methods and results are detailed. Finally, section 4 offers the conclusion and some policy remarks.

2 R&D Support Policies and Network Dynamics in Clusters

In the economic literature, the existence of market failures has traditionally been the main reason to support government intervention and public support for R&D (Westmore 2013, Busom i Piquer *et al.* 2015). Those market failures have mainly been produced by firms' underinvestment in innovative activities below what is socially desirable and optimal. Policy makers have increasingly called for robust empirical evidence to assess whether public intervention through innovation programs produces the effects necessary to circumvent these suboptimal levels of R&D investments, for instance, by stimulating and fostering firms' R&D efforts.

The impact assessment of public subsidies has been carried out in different ways. Many of the previous studies focus on the multiplier effects of R&D subsidies on the total amount of R&D expenditure (González and Pazó 2008) or if it could produce a crowding-out effect, whereby public funding replaces the private financing activities of the firms themselves (Busom and Fernández-Ribas 2008, Cerulli 2010). The concepts of input and output additionality are the most frequently used in policy evaluation (Clarysse *et al.* 2009). The additional amount of resources

Table 1: Innovation policies at a regional level

	DIRECT POLICIES		INDIRECT POLICIES
	R&D programs	**Collaborative programs**	
Main expected effect	Increase internal R&D expenditures	Foster alliances and relationships that foster knowledge exchange	Create a proper context for interactions between firms and institutions
Failure	Market	Market and System/network	Market and System/network
Main additionality	Input-output	Behavioral	Behavioral
Level of intervention	Firm	Network	Cluster
Cluster role	Not directly considered. Potential substituting effect (external instead of internal R&D)	Reinforcing role in establishing local and non-local connections	

Source: authors' elaboration

that subsidized firms invest in the innovation process is known as input additionality (Alecke et al. 2012), whereas output additionality refers to the additional outputs resulting from a policy intervention (Radicic *et al.* 2015). The scarce evaluation of cluster policies also focuses on this paradigm of R&D support and organizational results (Nishimura and Okamuro 2011, Martin *et al.* 2011).

As well as directly stimulating R&D efforts and innovation, there is growing interest in the promotion of co-creation of knowledge through collaborative agreements to stimulate innovation indirectly (Woolthuis *et al.*2005). From a regional perspective, there have been policies boosting local R&D collaborations and networks inside clusters, as a way to increase local innovation and to compensate for failures that appear as a consequence of the market's inability to procure an optimal level of knowledge production (Woolthuis *et al.* 2005). Under these policy initiatives lies the assumption, based on abundant empirical evidence, that localized learning based on the influence of spatial proximity on knowledge exchanges and socio-institutional factors rooted in the territory, provokes positive effects on innovation (Audretsch and Feldman, 1996, Malmberg and Maskell 2006) enabling comparatively higher innovation performance (Baptista and Swann 1998). Rather than considering that knowledge is "in the air" and available for everyone in the cluster, these policies stimulate the development of networks for knowledge exchange (Breschi and Lissoni 2001) since local buzz, of course, does not replace such networks. Moreover, collaborative R&D policies are needed, as firms have lower incentives to collaborate in networks due to the risk of diffusion and appropriation of valuable knowledge between their partners (Vicente 2014) as well as lock-in risk. This lack of formal collaboration is particularly relevant in clusters due to both the physical and cognitive proximity between firms that makes mutual understanding and knowledge exchange easier.

In trying to foster local collaboration, policy makers have undertaken direct policies related to the development of supporting organizations that would connect otherwise isolated firms (Belso-Martinez *et al.* 2018), as well as cluster-promotion programs (Martin and Sunley 2003). Moreover, there are collaborative R&D programs that aim to stimulate cooperation and partnership between firms and other institutions in the cluster (Caloffi *et al.* 2018).

However, regional policies, tailored to overcome sub-optimal firms' R&D efforts and innovation through pure R&D public-funded subsidies, can indirectly favour R&D collaborations to generate internal knowledge with complementary external knowledge for innovation. In other words, firm-level R&D subsidies can have an unexpected additionality effect, as it has been proved they foster collective creation of knowledge inside clusters (Martin *et al.* 2011, Nishimura and Okamuro 2011). In this sense, Nishimura and Okamuro (2011), focusing on the Industrial Cluster Project in Japan, confirmed that support program participants are more successful in networking within the cluster than others, thereby having a strong impact on innovation. Furthermore, cluster policies are effective in tackling network failures, enhancing both networking and knowledge flows (N'Ghauran and Autant-Bernard 2019). In a similar vein, Caloffi *et al.* (2018) compare the effect of firm-level R&D subsidies and cooperative R&D subsidies on networking effects, noting that policies that subsidize collaborative R&D do not perform better than policies that subsidize firm-level R&D, as both encourage networking.

Busom and Fernández-Ribas (2008) have also confirmed in their research on 716 Spanish firms, that R&D subsidies increase the chances of cooperation with other firms and supporting organizations.

Benefiting from R&D subsidies is not only conducive to higher internal R&D expenditures but also to collaborative agreements, as well as fostering the creation of new routines and capabilities that increase the participation of external networks inside clusters. As firms learn through internal R&D investments, they also develop their ability to understand and exploit external knowledge from local networks (Spithoven and Teirlinck 2015) and optimize the value of the knowledge acquired in terms of innovation (Lane *et al.* 2006). Moreover, as R&D subsidies attempt to compensate for lower internal R&D investments, they will also expand the range of firms undertaking R&D, broadening the range of participants from local networks, and providing new ideas, technologies and relationships that change existing local systems (Caloffi *et al.* 2018).

While these unplanned R&D collaborative effects from R&D programs could theoretically take place in any context, collaborative initiatives would enhance more effective knowledge creation and diffusion when they occur inside clusters (Munari *et al.* 2012). It is generally accepted that firms' ability to absorb external knowledge is influenced by spatial aspects, in relation to their geographical location (Storper and Venables 2004, Tödtling *et al.* 2011), where such absorptive capacity tends to be territorially generated and diffused (Audretsch and Feldman 1996, Malmberg and Maskell 2002). Firms that have R&D subsidies can establish collaborative activities with local partners more easily than with geographically distanced potential collaborators, as they can mutually understand and trust each other under the context of shared values, norms and assumptions of clusters (Belso-Martinez and Diez-Vial 2018). Based on that, we propose the following proposition:

> "In a cluster context, firm-level R&D subsidies have a positive impact beyond the firm and stimulate collaborative R&D networking"

Nevertheless, the measurement of the effect of R&D subsidies on the creation of relationships inside a cluster is complicated (Vicente 2014). Recent methodological contributions highlight the need to include Social Network Analysis (SNA) in the analytical toolbox for policy evaluation in clusters from a behavioral perspective (Giuliani and Pietrobelli 2016). In our case, its potentiality lies in enhancing our understanding of how R&D subsidies impact actors' decisions to deliberately form and preserve relationships (Vonortas 2013, Töpfer *et al.* 2019).

3 Empirical Setting and Research Methods

3.1 Empirical setting

3.1.1 The biotech industry

The research context is that of firms active in the biotech cluster of Alicante, located in the south of the Valencian region. Two main reasons motivate the selection of the biotech industry. First, it is one of the most innovative and knowledge-intensive sectors (Hagedoorn 1993), making it an ideal context for analyzing innovation processes and behavior. Particularly in Spain, the biotech industry has become one of the pillars of the economy (11 % GDP) due to its cross-cutting nature that allows firms from different sectors to incorporate biotechnology into their operations. Second, previous research mainly focuses on the effect of formal networks on biotech innovation (Powell *et al.* 1996) or its evolution (Gay and Dousset 2005), while the dynamics of the informal inter-firm linkages, sometimes underlying formal alliances, have traditionally been relegated (Salavisa *et al.* 2012).

3.1.2 R&D support in the Valencian region

The Valencian region is considered a representative model of regional development, mirroring the Italian "Emilian Model" (Antonioli *et al.* 2012), in which innovation policies are implemented through specific tools acting as public innovation enablers (e. g. public R&D expenditures or technological institutes). Together with the biotech cluster of Alicante, the region has other industrial clusters, technologically powerful in their respective industries (textile, footwear, tile, natural stone, foodstuffs, automotive, furniture, among others).

To support our arguments, we test the collaborative effects induced by an in-house R&D support program orchestrated by IVACE (Valencian Institute of Business Competitiveness).[2] The program, labelled Research and Technological Development Program (RTDP henceforth) promotes individual R&D within firms of different industries in the Valencian region, through firm-level projects carried out by the beneficiary of the subsidy. Two main lines of support comprise the RTDP: a) Subsidies to increase the

2 IVACE was created as a public body whose main aims are to manage the regional industrial policy, to support firms in innovation and to promote different technological enclaves (Holmström 2006).

capacity of firms to undertake R&D activities by facilitating the hiring of highly-qualified employees; b) Subsidies to foster R&D projects carried out by SMEs or supporting the creation of innovative firms. From 2004 to 2011, IVACE funded over 5,100 projects with 190 million euros, comprising a total investment of around 1,200 million euros.

3.1.3 Why the biotech cluster of Alicante?

A report drawn up in 2017 by the AEBA, a platform developed to enhance the awareness of the biotech cluster of Alicante, shows that the firms have 39.5 employees and an average turnover of 10 million euros. In terms of internal R&D, 33 % of the firms invest between 50,000 and 100,000 euros while the same percentage spends between 200,000 and 500,000 euros. Just 8.33 % of the firms invest more than 5 million euros, usually the leading firms, being the motor that drive the rest of the sector. Universities and technological institutes are the most common formal collaborators for cluster firms in the R&D field, 43.48 % and 30.43 % respectively. Public support for innovation activities is mostly obtained from IVACE (19.23 %), followed by the Centre for Industrial Technological Development (CDTI).

Two main reasons confirm the biotech cluster of the Alicante in the Valencian region as the ideal context to test our theoretical expectations regarding network dynamics. On the one hand, the geographical proximity around the metropolitan area of Alicante-Elche, fosters interactions of entrepreneurs or technicians, of either a formal or informal nature, to ask for advice about knowledge-based challenges that may not always be solved internally. In addition, the heterogeneity of the cluster activities (including red, white and green biotechnology) enables the exchanges of experiences in the access/use of technological facilities or in finding partners due to the lack of direct competition. On the other hand, the absence of any explicit external inducement to foster networking among local firms, such as public programs (Vlaisavljevic *et al.* 2020), provides a unique opportunity to map out the indirect effect of internal R&D public support. We reconstructed the cluster network based on informal advice seeking-giving among top managers and scientific entrepreneurs in the metropolitan area of Alicante-Elche. This approach is consistent with the territorialized structures of interdependencies for inter-organizational learning observed in the Spanish biotech industry (Cabello-Medina *et al.* 2020, Vlaisavljevic *et al.* 2020), and the relative prevalence of informal knowledge exchanges in Valencian biotech clusters compared to other geographies of the Spanish biotech industry (Vlaisavljevic *et al.* 2020).

3.2 Data collection

To test our hypothesis, we employed firm-level data gathered in the biotech cluster of Alicante by the end of 2013. From April to June, of the same year, we conducted 8 extensive interviews with managers, entrepreneurs and academics to achieve a refined picture of the cluster and the network dynamics in the industry. The information obtained was also applied to develop our survey and improve the discussion of our findings. Once pre-tested, our research team submitted our tool to representatives of the biotech firms located in the cluster. Interviews with top managers or business owners took about 45–50 minutes each. They collected data on firms' characteristics, innovation patterns, inter-organizational relationships, and performance.

The explicit objective of this paper requires both micro-level and network data. Therefore, we implemented the "roster-recall" method to detect inter-firm relationships. This methodology, in terms of the cluster's size and the procedure for the data collection, is suitable for the study. During the interview, a skilful technician showed respondents a roster containing all relevant firms located in the cluster and stimulated them to recall using examples of knowledge exchanges: i) from which firms in the roster they had received technological knowledge and ii) which firms in the roster had taken advantage of the transfer of technological knowledge by the firm. These questions are similar to those used in previous research (i. e. Giuliani 2013). A free recall area allowed respondents to include local partners omitted in the initial roster.

Data were collected on the entire universe of biotech firms that populated the cluster during 2013. Because of the inexistence of a particular database, we obtained a complete list of firms and organizations as a result of collating records from business associations, Bioval and AEBA. In the end, we identified 31 firms. Public institutions, such as universities, research centres, and hospitals that could play a relevant role in fostering international linkages, but were excluded from the survey. We wanted to evaluate mainly the role of R&D support in the dynamics of the local network, so they were excluded from the roster. Furthermore, a different methodological approach and conducting interviews with several managers and professionals would have been necessary if these large institutions had been taken into consideration. A total number of 28 firms accepted to answer the questionnaire, 90 % of the total sample.

The benefits of the project, the access to results (as an incentive) and the confidentiality guarantee, were explained at the beginning of the meeting in order to ensure the collection of accurate information data (Miller *et al.* 1997). During the interview, the skilled research team carefully explained the questions and provided examples for a better comprehension. Our research tool is capable of reducing potential flaws and bias. The structure, measures and clues incorporated in the questionnaire help to achieve reliable data. The reliability of the results was enhanced by restricting the scope to recent years, to aid recall, and by comparing the responses of willing and less willing participants, on the assumption that the unwilling participants proxy the views of those who refused participation. (Miller *et al.* 1997).

3.3 Network structure and sample descriptive statistics

Using the relational data, we constructed the technological knowledge network of the biotech cluster in Alicante. Information from 28 firms was used to build a squared matrix, where a cell takes value 1 if the firm i requested knowledge advice from firm j, and 0 otherwise. This resulted in a binary directed network structure, comprising 28 nodes and 55 edges. In this loose structure, actors share knowledge with about 2 other firms, the distance between firms is short and 5 firms remain isolated. Sometimes, even when data is based on a survey in which firms are asked about whom they ask for advice, such relationships are treated as undirected because partners always learn something from each other. However, we are confident with regard to the directed nature of the empirical relations observed, as only 9 % of the linkages show reciprocal knowledge flows.

Apparently, network representation reflects a sketchy, informal structure where the subsidized firms (20 %) are in light grey (see Figure 1). As far as the main descriptive statistics are concerned, the average number of employees and year since the inception are 21.82 (Sd=45.14) and 7.89 (Sd= 5.28) respectively, while the mean value for Non-local linkages is 1.14 (Sd=.54). In the next section, we explain the general principles of the statistical techniques that we used.

3.4 Statistical tool: ERGM

Exponential Random Graph Models (ERGMs) are used to incorporate properties of overall network structure, member attributes, and relational attributes to explain the differences between an observed network and a random network in the formation of linkages. We opted for these

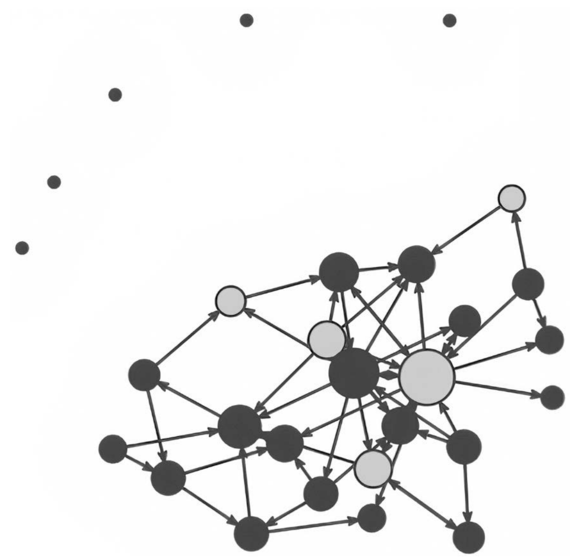


Figure 1: The local network of the biotech cluster of Alicante
Source: Authors' own data. Size of nodes is proportional to degree values.

models due to the violation of the assumption of independent observations and the opportunity to estimate the structural effects of the network on the incidence of ties.

The logic under the modelling can be explained as follows. The network obtained from the data collected is one specific case out of many potential network configurations (Morris *et al.* 2008). As we lack knowledge on how the observed network emerged instead of others, we assumed that firms create ties depending on a set of relational processes that reflect our theoretical hypotheses. Consistently, we built our ERGM by adding terms that reproduce these processes and should help to accurately replicate the observed network through simulation (Broekel *et al.* 2014).

The ERGM R-package, comprises a set of tools to simulate and diagnose networks applying exponential random graphs. The Monte Carlo Markov chain procedures (Hunter *et al.* 2008), allow these models to go a step further than the traditional SNA methods by accounting for complex network interdependencies. Although ERGM accounts for the complex network interdependencies, it produces models that are similar in structure and interpretation to a binary logistic regression model.

Compared to other Stochastic Actor-Oriented Models which require several time cohorts, ERGMs also explain the influence of node-level, dyad-level and network-level traits on link creation founded on data at just a certain point in time. Despite this advantage, only a few recent studies have applied ERGM on cluster knowledge networks (Broekel and Hartog 2013, Molina-Morales *et al.* 2015, Capone and Lazzeretti 2018, Juhász 2021).

3.5 Variables

Dependent variable
The dependent variable in our study is R&D collaborative network formation among our 28 cluster firms. To analyze the creation of linkages among our clustered firms, the dependent variable was built using used the observed relational data previously organized into an asymmetrical relational matrix, where each column i and each row j represent a firm. The cell input reflects whether or not there is a relationship between the firms in a binary form, containing the value of 1 if the firm i perceived an exchanged of knowledge with firm j, and 0 otherwise. Note that the asymmetric nature of the matrix is due to differences on the perception of the existence of knowledge transfers by each firm. Consequently, our model evaluates the relative contribution of a set of independent variables on the formation of the observed network structure.

Independent variables
In order to observe how internal R&D subsidies influence tie formation and knowledge sharing in clusters, we use node-level variables but also controls for several dyadic and structural effects. Node-level variables attain the impact of firm-level traits that influence tie creation. Dyad-level variables measure to what extent similarities between different organizations affect the likelihood that firms connect. Structural-level variables test the effect of the relational structure dependencies on the formalization of new ties.

Firm-level variables
The firm-level variable that tests our crucial theoretical expectation and captures to what extent a firm receives public support to promote internal R&D activities or not. Previous research, frequently applied dummy variables to test the influence of subsidies on firm's behavior (e. g. Nishimura and Okamuro 2011). So, our variable (*R&D subsidies*) takes a value of 1 if the firm obtained a subsidy from IVACE during the 3 previous years, value 0 otherwise.

Three additional firm-level characteristics were included. The establishment and maintenance of extra-cluster relationships allow the retrieval of novel knowledge (Bathelt *et al.* 2004, Bathelt and Turi 2011). Non-local linkages have been highlighted in the literature as an important source of new innovation opportunities at the local level and avoid lock-in (Bathelt *et al.* 2004). Firms with non-local linkages behave as gatekeepers of knowledge obtaining outside knowledge and disseminating it within the local collaborative network with the purpose of stimulating learning and sharing (Giuliani 2011). Using a 3 point-scale (0: local; 1: National; 2: International), we asked firms to report linkages with suppliers, customers, and competitors at the extra-cluster level. We then recorded the initial 3-point variable by dividing its sum by the maximum potential value, 6. Numerically, for each firm, this variable will range from 0 (local linkages only) to 2 (international partners in the three categories considered). The rationale underlying this variable (*Non-local linkages*) is that the greater the geographical distance and the diversity of actors, the greater the novelty of the knowledge accessed (Montoro-Sanchez *et al.* 2018).

Similarly to previous research in network dynamics in clusters (e. g. Juhász 2021), we controlled for the size of the firms using the number of employees (Size), because it may shape a firm's ability to procure knowledge in clusters. The prevalence of SMEs in our cluster makes this operationalization advisable, discouraging the use of alternatives such as market capitalization. The new firms may show different relational dynamics compared to experienced firms, due to lower resources (Molina-Morales *et al.* 2015); we controlled this influence through the number of years since creation (*AGE*).

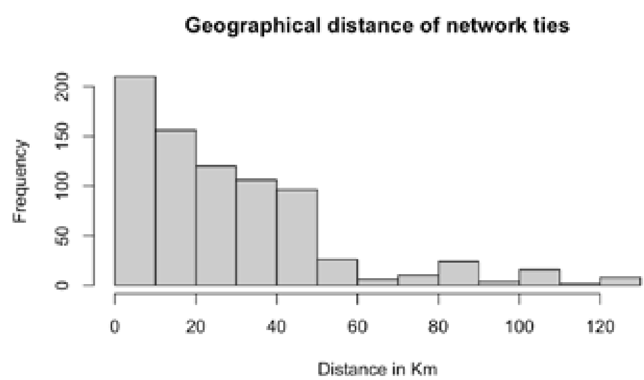


Figure 2: Descriptive statistics of geographical distance in the biotech cluster of Alicante
Source: authors' elaboration

Dyadic variables
Two variables were included at the dyad level. Cluster literature states that cooperation is more feasible when firms are geographically close to one another (Molina-Morales *et al.* 2015, Balland *et al.* 2016, Lazzeretti and Capone 2016). In our model, following Aguiléra *et al.* (2012), geographical proximity is operationalized as a binary matrix created by differentiating between ultra-local linkages (1: distance between partners is less than 5 km) and other local linkages (0: distance between partners is 5 km or more). Figure 2 presents the distribution of the geographical distance of the observed network ties.

Firms depicting similar technological maps are more prone to collaborate, as they can easily communicate and engage in common learning practices. Considering that cognitive similarity increases if firms join the same sector category, our *Cognitive proximity* variable was operationalized as a matrix built with the number of shared digits between the two firms in their 4-digit NACE codes (Balland *et al.* 2016). Regarding the cognitive proximity values for the sampled firms, 8.8 % share 4 NACE-digits, 3.3 % have 3 NACE-digits in common, 5.5 % present the same 2 NACE-digits and just 3.8 % shared 1 digit.[3]

Structural variables

To capture the role of network endogenous forces (Morris *et al.* 2008), we included the necessary structural parameters to control for density, degree distribution and triadic closure. Edges captures the network density effect, representing the average likelihood of tie formation between network members. A negative sign would show the reluctance of firms to engage in knowledge sharing. The term *Mutual* represents reciprocity and interdependencies in relationships. It is an indicator that firms symmetrically share knowledge for mutual benefit. The *Gwidegree* inversely weights the value of in-degree, the number of ties a firm receives, as an actor's count on the statistic increases. In marginal terms, the *Gwidegree* favours the addition of the second in-degree more highly than that of the tenth in-degree. A significantly negative *Gwidegree* indicates that prestigious firms in the network tend to attract many advice seekers based on expectations about the value of their knowledge stock (preferential attachment). The *Gwesp* relies on geometrically-weighted series to account for transitive closure, network tendency of "friends of a friend also become friends". Again, the probability of transitivity increases with each additional firm in common; it does so at a decreasing rate. A significantly positive *Gwesp* term represents more triadic closure within the network than is expected by chance (Goodreau et al. 2009). Also, we consider open triangular structures in the knowledge network including the parameter *Gwdsp*, which accounts for dyads with shared partners. It represents an indicator of multiple connectivity, reflecting the propensity of firms of being, at least, indirectly connected. When interpreted together, a significant positive value for *Gwesp* with a negative one for *Gwdsp* denote robust evidence for transitivity in the network (Hunter 2007). Transitivity is conducive to network cohesion, engendering shared norms and trust that facilitate knowledge exchanges. Finally, we add the statistic *Isolates*; equal to the number of firms with both in-degree and out-degree equal to 0. It accounts for the tendency of some actors to remain unconnected, evidencing the existence of alternative innovation strategies. Table 2 illustrates the different parameters together with their network effects and managerial connotations.

3.6 ERGM estimation and results

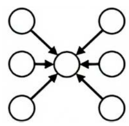
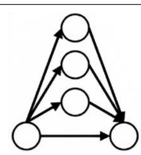
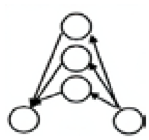
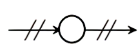
Our final model was developed in three steps. In the baseline model, we included the Edges and the different firm-level characteristics related with R&D collaborative network formation, particularly, non-local linkages and R&D subsidies. Two dyadic variables are included in the intermediate models to control how the effects of being geographically distant and cognitively proximate affect the evolution of our relational architecture. In our last model, structural network terms (Mutual, Gwidegree, Gwesp, Gwdsp) were entered to account for underlying structures often seen in social systems. Odds ratios and standard errors for all terms in each of the models are shown in Table 3.

According to coefficients in Table 3, R&D subsidies, Size and Non-local linkages are all positive and significant. As expected, firms with public innovation support tend to form more links. The relationship between the promotion of non-collaborative R&D activities through subsidies and the creation of collaborative linkages complement each other, generating synergies.[4] Firm size and non-local linkages positively relate to tie creation too, shaping the circulation of knowledge within cluster boundaries. On the one hand, large firms are more likely to engage in R&D collaborative networks. This is not surprising, as their solid resource base often facilitate the necessary capabilities to create local knowledge linkages. On the other hand, external connections are relevant to local knowledge sharing. The new knowledge accessed through non-local relationships and the visibility conferred to internationalize firms makes them more capable of cooperating.

3 The sub-sectoral structure of the sample was as follows: green biotech (39 %), red biotech (36 %), white biotech (11 %) and others (14 %).

4 When looking at the network plot, we observed that the firm with the largest degree of centrality had also been awarded R&D subsidies. To dissipate that our findings could be driven by this particular node, we further explore the degree centrality of the remaining four subsidized firms versus the non-supported firms. Once this firm was removed, the 87 % higher average degree reconfirms the validity of our results.

Table 2: Directed structural characteristics for ERGM, network effects and managerial implications

Statistic	Visualization	Description	Network effect
Edges		Sum of all ties in the network	Edge density. Models the average likelihood of tie formation between two actors within the network.
Mutual		Sum of all reciprocated ties in network	Reciprocity mechanism. Trend to tie creation based on interactions of giving and returning (mutuality).[5]
Gwidegree		In-degree distribution, accounting for decrease in marginal contribution of each additional tie received	Preferential attachment. Trend to network formation whereby well-connected actors are more prone to establish new ties.[6]
Gwesp		Transitivity distribution, accounting for decrease in marginal probability of closing triads.	Triangle closure mechanism. Trend towards linkage formation between two unconnected actors that share a common third.[7]
Gwdsp		Open triangles distribution, accounting for decrease in marginal probability for dyads with shared partners.	Multiple connectivity. Propensity of actors not directly connected to each other being at least indirectly linked.
Isolates		This term accounts for the number of isolated nodes in the network	Tendency of actors not to be linked to other network members

Source: authors' elaboration based on Hunter, *et al.* (2008) and Juhász (2021)

Table 3: ERGM estimations. Dependent variable: R&D collaborative network formation in the biotech cluster of Alicante

	Baseline model		Intermediate model		Full model	
	Coefficient	**(SE)**	**Coefficient**	**(SE)**	**Coefficient**	**(SE)**
Edges	***−4.751	(.665)	***−5.102	(.692)	***−3.865	(.748)
Size	***.008	(.002)	***.008	(.002)	***.007	(.002)
Age	.011	(.024)	.013	(.024)	.002	(.019)
Non-local linkages	*.418	(.241)	*.449	(.244)	.294	(.194)
R&D subsidies	***1.276	(.289)	***1.264	(.294)	***.921	(.299)
Geographical proximity			***.914	(.397)	**.751	(.352)
Cognitive proximity			.490	(.294)	.368	(.316)
Mutual					.310	(.575)
Gwidegree (.5)					−.180	(.658)
Gwesp (1.8)					**.289	(.130)
Gwdsp (1.2)					*−.141	(.086)
Isolates					**1.714	(.813)
AIC		355.3		352.3		350.6
BIC		378.3		384.7		406.1

***p<0.01; **p<0.05; *p<0.1

5 In lay terms, it is described by the aphorism "I will scratch your back if you scratch mine".

6 Often referred as "popularity is attractive" or "rich get richer" phenomenon.

7 In lay terms, it is described by the aphorism "friends of a friend become friends".

Table 4: Goodness of fit diagnostic for the final model

	Observed	Min	Mean	Max	P-value
Edges	55	34	56.610	82	.84
Size	4579	2325	4679.860	7410	.96
Age	926	546	947.890	1408	.88
Non-local linkages	149.333	88	53.273	221	.90
R&D subsidies	32	17	32.390	52	1.00
Geographical distance	11	4	49.970	18	1.00
Geographical proximity	15	7	15.090	26	.94
Mutual	6	1	6.560	17	1.00
Gwidegree (.5)	26.624	16.163	27.044	35.558	.90
Gwesp (1.8)	32.209	5.834	34.511	120.216	.94
Gwdsp (1.2)	134.122	46.397	141.736	281.135	.90
Isolates	5	1	4.940	11	1.00

The dyad-level variable geographical proximity is characterized by a significant coefficient. Hence, in line with existing empirical evidence (Molina-Morales *et al.* 2015, Balland *et al.* 2016, Lazzeretti and Capone 2016, Juhász 2021), geographical proximity fosters link creation. Regarding the factors at the structural level, the negative coefficient of Edges reflects the natural tendency of social networks to be less dense than exponential random networks (Broekel and Hartog 2013), and may reflect the reluctance of local firms to establish linkages with other network members. The positive and significant value of *Gwesp* implies that triangles are a common feature of the network, and triadic closure is a mechanism of network formation. In other words, firms connected through direct linkages are more prone to be also tied through indirect relationships (Broekel and Hartog 2013, Molina-Morales *et al.* 2015, Juhász 2021). The negative and significant *Gwdsp* indicates that unlinked firms are generally unlikely to have shared a link with other firms (Juhász 2021). Once firm-level characteristics are accounted for, there is an overall lack of structural similarity in the network. Combined with *Gwesp,* this evidence of multi-connectivity supports the relevance of transitivity as a mechanism of network formation.

We now turn to the analysis of the variables with insignificant coefficients. The lack of statistical relevance of firm age implies that the number of years since the firm's creation does not increase the probability of knowledge sharing, in line with findings by Juhász (2021) but contrary to Molina-Morales *et al.* (2015). Although a common knowledge base and expertise have been proved to enable firms' engagement in knowledge sharing (Balland *et al.* 2016, Lazzeretti and Capone 2016), cognitive proximity did not achieve the predicted relevance. In line with recent findings (Juhász 2021), our results suggest differences among sectors regarding the effect of cognitive proximity on tie formation. The preferential attachment logic observed by Menzel *et al.* (2017) is not confirmed, as *Gwidegree* is not significant. The positive isolation effect indicates that some firms are uninvolved in the creation of knowledge linkages, indicating the potential existence of alternative knowledge generation in which individual firms unilaterally recombine pre-existent pieces of knowledge. Finally, we do not corroborate the importance of reciprocity found by Giuliani (2013), which we reflected in the Mutual variable.

Regarding Goodness of fit (GOF), the final model is stable and converges. Due to the dependent nature of our data, traditional measures of model fit such as the Aikake information criterion were discarded (Hunter *et al.* 2008). Instead, GOF statistics and plots were used. The limited differences between the observed network and simulations from the final model indicate a good match (see Table 4). In addition, the plots also show a good fit between the observed and the simulated networks as the black lines representing the observed network all fall in the 95 % confidence intervals.[8]

4 Discussion and conclusions

The assessment of the results obtained by the regional public intervention in R&D is a complex task, due to the heterogeneity of projects, recipients and purposes (Busom *et al.* 2014, Busom i Piquer *et al.* 2015). This reality under-

8 P-values close to 1 indicate a good match between the observed and the simulated network. In addition, a good fit between the observed and the simulated networks were done and can be provided by the authors upon request.

lies the open debate on the effects, justification, benefits, and timing of cluster policies (Abbasiharofteh 2020, Graf and Broekel 2020). Notwithstanding the value of traditional evaluation based on the input-output approach, they relegated important effects at network or systemic level that help to achieve a more accurate picture of the policy effects.

This paper contributes to this debate by focusing on the behavioral additionality of non-collaborative R&D subsidies. In line with previous findings based on collaborative R&D programs (Nishimura and Okamuro 2011, Busom and Fernández-Ribas 2008, Wanzenböck *et al.* 2013), we observed that subsidized firms show a different networking behavior in clusters. However, what makes our research outstandingly attractive is the significantly positive and stimulating impact of public R&D funding on R&D collaboration even though the funding was at the firm-level with no focus on inter-firm interaction. This indicates the enormous synergies in clusters that result from local buzz and spill-overs and make such configurations competitive and innovative places. So, this side effect should be observed when considering policy results.

This outcome has noteworthy implications from both an R&D policy and a cluster perspective. Clusters are complex systems made up of interdependent and interacting members that engender self-organized organic structures. Our generic R&D subsidies amending market and/or system failures, reinforce the cluster's collaborative networking dynamics and the position of larger incumbent firms. This is often conducive to low-risk and low additionality innovation practices, which exploit pre-existent local knowledge.

In order to test the effect of non-collaborative R&D on network behavior, we use a novel methodology based on SNA. Our research evidence reveals that SNA represents an essential tool for the evaluation of innovation policies. To the best of our knowledge, our ERGM is a pioneering attempt to map out network dynamics due to non-collaborative R&D support while controlling for dyadic and structural effects. Its outcome provides additional evidence on how innovation policy may collaterally affect information flows within a network (Vonortas 2013, Töpfer *et al.* 2019).

Despite the unquestionable value of alternative forms of geographical proximity, the role of permanent collocation is invaluable. In line with existing empirical evidence, geographical distance hinders link creation, and for instance, the opportunity to raise positive externalities in clusters, especially in innovation (Geldes *et al.* 2015) and for interaction, rapid diffusion of ideas and knowledge spillovers (Audretsch and Feldman 1996). On the other hand, the lack of significance of cognitive proximity insinuates that repositories of novel or complementary knowledge from cognitively distant co-located firms represent suitable collaborative alternatives. However, as Balland (2012) pointed out, this outcome largely depends on the operationalization of the variable, and alternative measures may lead to different results. In short, two reasons may help to explain this finding: the contextual nature of the cluster selected and the need for alternative operationalization of cognitive proximity (Huber 2012).

Moreover, we have observed that non-local connectedness favours the creation of intra-cluster relationships. This result is in line with previous findings on the role of the gatekeepers of knowledge as catalyzers and disseminators of novel knowledge (Giuliani 2011), and the need to engage within the local network to exploit external knowledge (Bathelt *et al.* 2004). This reinforces the undisputed importance of cross-border knowledge for clusters, and the complementarity of local buzz and global pipelines for the viability of clusters as hot spots of knowledge creation and innovation. Our findings reveal a positive effect of size as a significant mechanism for generating ties. A solid resource base facilitates the creation and management of networks, which provides opportunities to further enlarge the firm's knowledge endowments. In the light of our preferential attachment results, networking does not seem to be systematically driven by popularity. Perhaps, the influence of solid resources and knowledge for tie formation overshadows or replaces the rich-get-richer mechanism.

For policy makers, our study provides guidelines for the design and evaluation of R&D programs. The concurrent implementation of the input-output and behavioral approaches allows a more refined picture of the real policy impact at both firm and systemic levels. This is of particular value in clusters where unexpected emergent strategies derived from policy implementation may result in changes that would be beneficial (or not). The indirect enhancement of network density may foster knowledge access at the firm level, while engendering systemic over-density and lock-in. These findings also have managerial implications. Non-collaborative R&D through public subsidies shapes inter-firm cooperation, particularly in clusters where cooperation and trust prevail. Top-level managers should be conscious of the additional benefits that these R&D subsidies may have in developing cooperation agreements with collocated firms. These subsidies can provide an opportunity to not only become more innovative but also to develop more valuable assets and routines in inter-firm relationships.

This research is not exempt of some limitations that open avenues for future research. Care should be taken when generalizing our findings. We collected data from a single biotech cluster during a stage of its life cycle, ex-post analysis. Our findings and implications may significantly change when other clusters or different stages of the cluster's lifecycle are considered (Abbasiharofteh 2020). Also, despite the advanced methodological approach applied, our cross-sectional analysis would gain solidness with the inclusion of more time cohorts and alternative methods (e. g. Stochastic Actor Oriented Models). Population and cluster size are similar to those found in previous research, but adding more subsidized firms or widening the programs considered would enhance the robustness of our results. In line with Lee & Monge (2011), who offer an illustrative example on how linkages in a network of implementation of R&D projects may affect the creation or extinction of ties in a network of knowledge-sharing projects, more sophisticated ERGM configurations will provide us the opportunity to analyze how linkages in one knowledge network (e. g. technical) may shape the evolution of ties in a different knowledge network (e. g. business) at the cluster level. Lack of data forced us to use size as the number of employees. Particularly in the biotech industry, alternative operationalizations- such as market capitalization- would procure a more robust control. Finally, future research should consider the role of universities and other supporting organizations within the sample collected, developing specific questionnaires and contemplating relational portfolios. In our case, the focus of our analysis was on firms and 90 % of these firms recognized knowledge linkages with local universities.

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