

## Knowledge specialization and R&D collaboration

This is the peer reviewed version of the following article:

*Original:*

Caminati, M. (2016). Knowledge specialization and R&D collaboration. JOURNAL OF EVOLUTIONARY ECONOMICS, 26(2), 247-270 [10.1007/s00191-016-0449-5].

*Availability:*

This version is available <http://hdl.handle.net/11365/991123> since 2016-04-24T16:16:38Z

*Published:*

DOI: <http://doi.org/10.1007/s00191-016-0449-5>

*Terms of use:*

Open Access

The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. Works made available under a Creative Commons license can be used according to the terms and conditions of said license.

For all terms of use and more information see the publisher's website.

(Article begins on next page)

2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

# Knowledge specialization and R&D collaboration<sup>1</sup>

Mauro Caminati<sup>2</sup>

Department of Economics and Statistics DEPS, University of Siena

February 11, 2016

<sup>1</sup>Preliminary drafts of this paper have been presented at the EAEPE annual Conference, Krakow, 18-21 October 2012, and at the CICSE Conference, "Structural Change, dynamics and economic growth", Livorno, 12-14 September 2013. Special thanks are due to Vincenzo Lombardo and two anonymous referees for stimulating comments and constructive criticism on a previous version of this paper. Financial support from MIUR, Italy is gratefully acknowledged.

<sup>2</sup>e-mail: caminati@unisi.it; fax-number: +39 0577 232661

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

## Abstract

This paper contributes to the knowledge-based explanation of R&D networks. It argues that knowledge overlap and novelty are complementary inputs of a R&D alliance, in forms that depend upon the exploration breadth and depth of the R&D activity. The paper investigates how the hypothesis of specialization of the knowledge endowments can recover a number of characteristic empirical properties of a pattern of R&D collaboration in the economy. Implications for network evolution are discussed.

*JEL classification:* D85, O30

*Keywords:* relative knowledge proximity, radical and incremental R&D, competence communities, pooled and non-pooled R&D networks, network modularity

# 1 Introduction

The R&D alliance is documented by a large body of evidence, concerning most notably the industrial sectors in which the pace of technological progress is faster (Hagedoorn 2002, Powell et al. 2005, Roijakkers and Hagedoorn 2006). Generically motivated by a sharing of resources, a less generic, and often crucial motivation is the sharing and interaction of the heterogeneous competences residing with different organizations: public R&D laboratories, firms, units of a large company (Nooteboom 2000b, Hansen 2002). R&D networks reach greater diffusion in those fields in which innovation bears closer roots in abstract and codifiable knowledge. Pharmaceuticals (Orsenigo et al. 2001, Krafft et al. 2014), biotechnology (Powell et al. 1996, Gisling and Duysters 2008), and the ICT's (Cloudt et al. 2006, Hanaki et al. 2010) are prominent examples. Beyond producing faster and more accurate communication, codifiability may elicit the near decomposition of knowledge into building blocks (Holland 1992, Frenken et al. 1999). This promotes the innovative recombination of ideas (Fleming and Sorenson 2001), the division of inventive labor, and the decentralization of R&D activities across organizations (Arora and Gambardella 1994, 2010). Innovation alliances have been growing in importance in the last decades of the 20th century, but somewhat decayed thereafter (Gulati et al 2012).

The vast empirical literature addressing the structure and evolution of real-world innovation networks in specific industries and/or geographic areas<sup>1</sup> often borrows tools from social network analysis (Krafft et al. 2011, Cantner and Graf 2006). Further insights are offered by large-scale investigations of R&D alliances addressing a large multiplicity of sectors (Shilling and Phelps 2007, Tomasello et al. 2013) and/or regions (Fleming et al. 2007).

Drawing upon this empirical work, a broad picture emerged highlighting a number of regularities in the properties of R&D networks that resist some evidence of cross-sector variation<sup>2</sup>: *(i)* The fraction of one's collaborators that cooperate with each-other is high, thus leading to a high relational clustering (transitivity) of connections. *(ii)* R&D networks are organized to form a small-world structure (Fleming and Marx 2006, Uzzi et al. 2007). Most intuitively, this means that, on average, an organization is linked to any other by a small number of relational steps, in spite of the fact that every organization is directly linked only to a small fraction of others. *(iii)* At a multi-sector scale of analysis (but not a lower scale, cf. Tomasello et al. 2013), the highly connected R&D units are more frequently linked to other similar units than a random wiring of connections would suggest (positive assortativity by degree). *(iv)* The distribution in the number of R&D collaborations (showing how the fraction of nodes relates to the number of links) is asymmetrical. Most nodes have a smaller than average degree, and a small, but non negligible fraction of nodes have a large number of connections. This makes the degree distribution positively (right)

---

<sup>1</sup>This paper abstracts from the geographic dimension of R&D networks, and from any correlation of geographic proximity with relational proximity. This correlation may partly depend on the sector concerned (Orsenigo 2006).

<sup>2</sup>Rosenkopf and Schilling (2007, 2012); Tomasello et al. (2013).

skewed<sup>3</sup>.

Different lines of theorizing have been used to explain the formation and evolution of R&D networks. Arguments borrowed from social-capital theory suggest that partner selection is influenced by the pre-existing pattern of strategic alliances: to mitigate the risks inherent in interfirm relations (Oxley 1997), organizations are inclined to confirm to their past successful interactions. The resulting accumulation of trust and reputation facilitates the formation of alliances between firms collaborating with the same partner. Clustering and inertia in the pattern of inter-firm relations are a consequence (Gulati 1995, Gulati and Gargiulo 1999). The clustering of network relations gives rise to brokerage opportunities (Burt 1992): a firm can reap intermediation rewards whenever it channels relevant information between two otherwise disconnected regions of the network. The hypothesis that the clustering of R&D alliances produces incentives to the formation of clique-spanning ties (Walker et al. 1997) is consistent with the formation of small-world R&D networks (Baum et al. 2003).

Another branch of the literature addresses the complex strategic interactions arising from situations in which the same firms cooperating in R&D are competitors in the market for output. The forms of competition prevailing in this market are thus consequential to R&D alliances (Goyal and Moraga-Gonzales 2001, Goyal and Joshi 2003, Dawid and Hellmann 2014).

This paper contributes to a third line of explanation, which makes full abstraction from social capital arguments, and from concerns relating to the forms of competition in the market for output. The formation of R&D alliances is explained by the size and composition of technological-knowledge portfolios. This hypothesis receives empirical corroboration in Mowery et al. (1998). In what follows, strategic behavior is simplified by the assumption that alliance formation is not directly influenced by network topology: the duration of a partnership agreement is sufficiently short that potential knowledge spillovers from indirect partners do not materialize within the unit time interval, and do not affect partner selection<sup>4</sup>. All information relevant to alliance formation is embodied in the given distribution of the knowledge portfolios: this simplified approach is developed to suggest that the relative similarity/dissimilarity in the composition of the knowledge bases of two potential partners determines their incentives to collaborate on more incremental/radical R&D projects. More incremental R&D is focused on a deeper search in a small neighborhood of the known ideas; more radical R&D extends the breadth of search far from the accumulated competences; new ideas may be discovered through a widening and transforming of the search space. In this perspective, the R&D organizations in one industrial sector

---

<sup>3</sup>In the so-called 'scale free' networks, asymmetry takes the more specific form such that the degree distribution approximates a power-law: node frequency decays linearly with node-degree on a log-log scale (at least in a relevant range of the distribution). This feature is also revealed by some R&D networks (see Powell et al. 2005).

<sup>4</sup>Assumptions to the same effect are implicit in Cowan and Jonard (2009), Blum et al. (2014) Egbetokun and Savin (2014). By contrast, network topology affects alliance formation if long-lasting partnership agreements are formed to maximize the net benefits from the knowledge spillovers flowing through one's direct and indirect connections (König et al. 2011).

are members of a competence community, collaborating with members of the same, and of other communities, on various types of R&D projects. The paper claims that some empirical regularities of R&D networks are better understood by taking a multi-sector perspective on R&D collaboration.

The suggested model brings into sharper focus some potential sources of link instability that may result from the processes of knowledge convergence and divergence between former partners. It is shown that network instability may be triggered by specific local topologies of links. Insights on the historical evolution of innovation networks are finally discussed.

The paper is organized as follows. Section 2 presents the theoretical framework and relates it to the literature on R&D networks. Section 3 contains the analysis and motivation of model structure, followed by a description of the results in section 4, and by discussion in section 5. Summary conclusions are offered in section 6.

## 2 Theoretical framework and relations with the literature

This paper bridges different strands of the literature on innovation and R&D collaboration. It holds to the general tenet that knowledge grows through the creative recombination of ideas (Holland 1992, Kauffman et al. 2000, Reiter 2001, Weitzman 1998)<sup>5</sup>, and, for the sake of simplicity, it makes full abstraction from tacit knowledge<sup>6</sup>. A codifiable technological idea, or design, is a binary string  $\mathbf{a} \in \{0, 1\}^N$  of  $N$  elements. Each element  $a_n$  is identified by its position  $n$ , and corresponds to a knowledge component, which may be active ( $a_n = 1$ ), or silent ( $a_n = 0$ ). In this interpretation, a design maps to a list of product functions/characteristics, that is to a set of phenotypic traits. An innovation is the discovery that a previously untried idea maps to a set of phenotypic traits leading to a better performance. As with Kauffman (1988), Caminati (2006), Krafft et al. (2014), we allow for the fact that the number  $N$  of components will change through time as a result of radical innovations. A radical discovery is obtained through a redefinition and dimensional growth of the space in which ideas are defined.

This paper is focused on the way an exogenously given pattern of knowledge specialization in the economy is reflected in a pattern of R&D collaborations within and between competence communities. Sharing the same sector of activity entails affiliation to a knowledge community, the ideas of which are defined in a specialized competence field, a strict subset of the knowledge space. Though different fields will normally share a number of knowledge dimensions, ideas are expected to have a more coherent (Nesta and Saviotti 2005) and similar (Krafft

<sup>5</sup>A wider reference list in Frenken (2006), Antonelli et al. (2010).

<sup>6</sup>Lane et al. (1996) expands on 'generative relationships' in environments characterized by strong uncertainty and tacit knowledge.

et al. 2014) string composition, and a lower distance<sup>7</sup>, if they are selected from a more specialized competence base. Knowledge depth defines the extent to which a knowledge base is focused on a particular domain. Knowledge breadth defines the extent to which ideas may belong in different domains, and the average distance between them is high (Wu and Shanley 2009, Cohen and Levinthal 1990).

March’s (1991) distinction between exploitation and exploration is generalized in what follows in ways that are reminiscent of Bogenrieder and Nooteboom (2004). Going beyond a dichotomous bipartition of activities, for instance, production versus research, we refer to multiple levels of exploration, such that exploration at the higher level broadens the framework, and cuts loose from (some of) the constraints that are held fixed in exploration at the lower level. Drawing on Kauffman et al. (2000), we assume that such constraints can be defined in terms of the distance between one’s knowledge base and the new ideas under exploration. We assume a potential continuum of exploration levels. Searching at a short distance amounts to searching at great depth within a specialized field. In this case, the variance of exploration outcomes is predictably low, because a large majority of components is unchanged. Conversely, searching at high distance confers breadth to exploration, producing a larger variance of search outcomes (Fleming and Sorenson 2001). The greater (lower) the fraction of effort spent searching at a short distance, the greater the incremental (radical) nature of exploration.

The opportunity to discover new ideas grows with the number of the recombination possibilities (Weitzman 1998), hence with the variety (Saviotti 1988), embodied in one’s knowledge repertoire. On this ground, we assume that an R&D organization  $i$ , with a knowledge endowment  $\mathbf{A}_i$  of size  $K_i$ , is willing to form an R&D coalition with a potential partner  $j$  only if there are ideas in  $\mathbf{A}_j$  that are not contained in  $\mathbf{A}_i$ . To make this novelty contribution effective, it is also necessary that  $i$  shares with  $j$  a background of common understanding. This argument is related to, but does not coincide with, the notion of an optimal cognitive distance between R&D partners (Nooteboom 1992, 2000, 2004). According to Nooteboom, if cognitive distance is too low, interaction does not lead to any substantial gain in competence or creativity (novelty is too low), and if it is too large, the potential gain is inhibited by the lack of understanding. The outcome is a inverse-U shaped relation between one’s collaboration pay-off, and the cognitive distance with respect to a potential partner<sup>8</sup>.

The focus on cognitive distance has the drawback that it conveys, perhaps unwittingly, the intuition of a symmetric distance relation. While holding to the view that R&D collaboration is rooted in a mutual contribution of new ideas, this paper makes the point that this contribution, and collaboration incentives,

<sup>7</sup>The distance between two ideas  $\mathbf{a}$ ,  $\mathbf{a}'$  is the number of components  $n \in \{1, 2, \dots, N\}$ , such that  $a_n \neq a'_n$ .

<sup>8</sup>A recent attempt at empirical corroboration of an inverse U-shaped relation between firm innovation success, and cognitive distance with respect to R&D partners is Wuyts et al. (2006). Some ‘empirical proxy-measures’ of cognitive distance (Nooteboom 2000, p. 301, Nooteboom et al. 2007) are closer to a notion of ‘knowledge overlap’.

are generally non-symmetric between partners. (For a different treatment see Cowan and Jonard 2009, Egbetokun and Savin 2014.)

The simplest formalization of the novelty contribution of a unit  $j$  to a partner  $i$ , is the count  $\lambda_{ij}$  and  $n_{ij}$  of how many ideas of the former are, and are not already known by the latter:

$$\lambda_{ij} = \# \{ \mathbf{A}_i \cap \mathbf{A}_j \} \quad (1)$$

$$n_{ij} = \# \{ \mathbf{A}_j - \mathbf{A}_i \cap \mathbf{A}_j \} = K_j - \lambda_{ij} \quad (2)$$

where  $K_j \geq K_i$  implies  $n_{ij} \geq n_{ji}$ . Relative novelty  $n_{ij}$  and overlap  $\lambda_{ij}$  can be expressed as a ratio of endowment size  $K_j$  to yield novelty ratio  $D_{ij}$  and proximity ratio  $p_{ij}$ .

$$D_{ij} = \frac{n_{ij}}{K_j}; \quad p_{ij} = \frac{\lambda_{ij}}{K_j}; \quad D_{ij} = (1 - p_{ij}) \quad (3)$$

The measure  $p_{ij}$  yields coarse-grained information on relative knowledge similarity, based on the co-occurrence of ideas in  $\mathbf{A}_i$  and  $\mathbf{A}_j$ . If one looks at the co-occurrence of building blocks of components, not just of ideas, relative knowledge similarity is then assessed by fine-grained standards<sup>9</sup>. This complication was avoided because, in the present context, it would not change the nature of the results.

R&D organizations may be business firms, private or public R&D laboratories, or university research centers (Saviotti 2009). Such a differentiated set of actors is characterized by different motivations and incentives. On the ground that this paper is focused on the knowledge-based incentives, that the incentives in question are of a general nature, and that the properties to be explained extend across different domains of R&D activity, ontological differences between the different actors will be disregarded. They are considered as individual decision centers, and full abstraction is made of their internal structure: they will be equivalently referred to as units, or agents.

The formation of alliances will be studied under the weak requirement that a network is a *pairwise stable equilibrium* (Jackson and Wolinsky 1996) of the collaboration game (Vega-Redondo 2007, Goyal 2007, Jackson 2008) corresponding to a given distribution of knowledge.

This paper argues that partner and project selection in R&D is restricted by the similarity in the composition of the knowledge base. The resulting restrictions produce (i) the transitivity of R&D alliances connecting members of the same competence community, and (ii) the near-decomposable modularity of a R&D network pooling a multiplicity of sector communities. The combination of these properties explains that multisector R&D networks obey the small world

---

<sup>9</sup>Fine-grained measures have been introduced to characterize distribution of patent classes/sub-classes in a population of patents (Breschi et al. 2003, Nesta and Saviotti 2005, Krafft et al. 2014), or the frequency of design selection in a population of users (Frenken and Nuvolari 2004). Our aim is partly different here, because we need to characterize the properties of a knowledge base, *relative* to another.



property, and are similar in structure to other social networks. These concepts are briefly clarified in the sequel (formal details in appendix).

The transitivity of a pattern of R&D alliances is measured by the network average of the fraction  $C_i$  of  $i$ 's R&D partners that cooperate with each-other. The local clustering coefficient  $C_i$  is not well defined for the nodes of degree zero and one. For this reason, the average clustering coefficient  $C$  is often replaced by the global clustering coefficient  $C_N$  (Newman 2010, p. 199):

$$C_N = \frac{\text{number of fully connected triplets of nodes}}{\text{number of connected triplets of nodes}}$$

To measure the extent in which network transitivity is not merely explained by the density of connections<sup>10</sup>,  $C_N$  is weighted by the global clustering coefficient  $C_N^R$  of a network of identical size and node-degree (number of links) distribution, but with a random wiring of connections. High clustering implies a local redundancy of links, that is, a multiplicity of connecting pathways between the nodes in the same cluster. The attached interpretation is that redundancy increases the speed and quality of information transfer (Shilling and Phelps 2007).

The modularity of a network (Newman 2006) connecting a set  $\mathbf{H}$  of agents is a measure of the extent in which the set  $\mathbf{H}$  can be endogenously partitioned into  $M \leq H$  groups with the aim of maximizing the average difference between the *ex-post* frequency of collaboration with a member of the same group, and the expected frequency that would result from a random wiring of connections. Modularity is high, if and to the extent that there exist partitions such that the average frequency of connection within the groups is high, and the average frequency of connection between the groups is low. For given  $M$  and  $H$ , modularity is maximal if all the existing links remain within the groups, in which case the network is decomposable into disconnected sub-networks. In the presence of weak links between the groups, modularity leads to near-decomposability (Simon 2005, Frenken et al. 1999).

To the extent that a large multi-sector R&D network has a highly transitive, near-decomposable pattern of connections, it is likely to conform to the small-world property; moreover, the high degree nodes tend to be connected with other high-degree nodes (assortativity by degree is positive).

A small-world (Watts and Strogatz 1998, Watts 1999) is, most intuitively, a network combining high local clustering with sparse clique-spanning ties: weak connectivity between the clusters makes the ratio between network average degree and size lower than otherwise; simultaneously, clique-spanning ties preserve the possibility that, on average, a node in the network can reach any other in a small number of connection steps (see appendix). As a matter of interpretation, between-group connections are formed by organizations with more heterogeneous knowledge bases (Fleming and Marx 2006, Fleming et al. 2007). Such connections are most likely non-redundant, and provide a source of novel ideas, which contribute to preserving knowledge heterogeneity within a group (Uzzi et al. 2007).

---

<sup>10</sup>If a network is fully connected,  $C_N = 1$ .

A pattern of R&D alliances pooling connections formed by members of different competence communities is predicted to share the same characters of ten distinguishing socio-economic networks from networks in other domains<sup>11</sup>: higher clustering, sharper small-world property, and positive assortativity by degree. According to Newman and Park (2003), the above distinguishing features result from a single unique property of social actors: that of being typically embedded in one or more social communities (professional, religious, cultural, etc.) affecting the pattern of their relations. The event that agents  $i$  and  $j$  are members of the same social group makes the probability of a link  $ij$  between them higher than average. On this premise, the authors can show that positive assortativity by degree and high clustering within groups are related properties.

What follows offers a modification and mild generalization of this argument. The main claim is that the knowledge-field specialization of R&D organizations, and the variation of R&D activity along the dimensions of breadth and depth, produces the patterns of transitivity, modularity, degree-assortativity, and small-world characterizing a multi-sector R&D network. The model predicts that a pooled R&D network more closely approximates the typical structure of a social network than any of the sector networks of which it is composed. This prediction offers a key to interpret the empirical evidence offered by Tomasello et al. (2013).

In spite of its static nature, the model also bears a number of implications concerning the forces explaining change in network structure through time. The historical development of R&D alliances in the decades after 1980 can be divided into a growing phase that reached its peak in 1994-1997, followed by a decaying phase (Tomasello et al. 2013, Gulati et al. 2012). The tendency to a local and global increase in the density of R&D alliances was marked by the formation of a large giant component. The tendency was reversed in the second phase, leading to a more fragmented network.

Our results may contribute to the interpretation of R&D network evolution on two accounts. In the first place, the phase of network growth is associated with the diffusion of information and communication technologies after the 1980's, through the effects on the collaboration cost. In the second place, the severance of R&D links is favored by local topologies of R&D alliances, which prevent stabilization of between-partners differences in the composition of knowledge. The paper provides a multi-sector perspective to some interpretations of network decay (Cowan et al. 2006, Cowan and Jonard 2009, Baum et al. 2014), and their application to the falling phase of R&D alliance after 1997 (Tomasello et al. 2013, Gulati et al. 2012).

### 3 The model

This section specifies the model of R&D collaboration that is the backbone of the analysis in this paper. Presentation of the initial allocation of knowledge

---

<sup>11</sup>Biology, ecology, technology are the main examples (Caldarelli 2007).

endowments is followed by model specification and a preliminary discussion of its properties. Results are spelled out in the following section.

### 3.1 Competence communities

In the social and economic domains, network participants are often qualified by their affiliation to a group or community. Firms exert their activities in some industrial sector, scientists, technicians and engineers are affiliated with professional associations and orders, R&D laboratories register their patents in one or more technology classes. A community structure is a list of subsets  $\{\mathbf{H}_1, \dots, \mathbf{H}_W\}$  of  $\mathbf{H}$ , such that  $\cup_{w=1}^W \mathbf{H}_w = \mathbf{H}$ , and the members of the same group  $\mathbf{H}_w$  share a common property. If group affiliations are mutually exclusive, the community structure is a partition of  $\mathbf{H}$ .

An exogenous community structure is introduced by assuming that  $\mathbf{H}_w$  is the community of specialists, with ideas defined in the same competence field  $\mathbf{X}_w$ , defined by a maximal set  $\mathbf{Z}_w \subset \{1, \dots, N\}$  of active dimensions. If  $\mathbf{a}$  is defined on  $\mathbf{X}_w$ , and  $n \notin \mathbf{Z}_w$ , then  $a_n = 0$ . Of all ideas defined in a competence field, only a subset of cardinality  $\Psi$  is known. Every  $i \in \mathbf{H}$  is then randomly assigned every known idea defined in  $i$ 's competence field with uniform probability  $p = 0.5$ , and every known idea outside this field with probability zero. The expected size of  $i$ 's initial endowment  $\mathbf{A}_i$  is then given as (see appendix):

$$E(K_i) = \frac{1}{2}\Psi \quad (4)$$

The uniform probability assumption yields a symmetric size distribution of the knowledge endowments, which does not have an empirical motivation but reflects the spirit of the present exercise: network formation is envisaged in a hypothetical initial setting, making full abstraction from any antecedent process of network growth.<sup>12</sup>

For a fixed choice of  $\Psi$ , we assume a 'representative' allocation of endowments  $\mathbf{A} = \{\mathbf{A}_i, i \in \mathbf{H}\}$  induced by  $\Psi$ , under the endowment assignment rule described above. A representative allocation of endowments is defined by properties that obtain with sufficiently high probability, on the assumption that the number of ideas in a competence field and the number of units in a knowledge community are large enough (see appendix).

We are interested in comparing the implications following from two articulations of the community structure. In one framework  $W > 1$ , and  $\mathbf{H}$  is partitioned into a multiplicity  $W$  of competence communities  $\{\mathbf{H}_1, \dots, \mathbf{H}_W\}$ , each producing a sector network  $\{\mathbf{H}_w, \mathbf{L}_w\}$ , with  $\mathbf{L}_w$  indicating the set of links connecting the members of  $\mathbf{H}_w$ . The corresponding pooled network  $\{\mathbf{H}, \mathbf{L}\}$  describes the union of all within-field and between-fields alliances.

A second framework assumes  $W = 1$ , yielding a non-pooled  $\{\mathbf{H}, \mathbf{L}\}$ . This serves the purpose of comparing the properties of pooled and non-pooled networks, abstracting from differences that are merely dependent on size. It may

<sup>12</sup>This excludes the asymmetry of the degree distribution from the domain of explanation of this paper.

be worth stressing that, in the framework of nested networks, pooled and non-pooled are only a matter of degree. A sector network is itself pooled, relative to the sub-networks corresponding to the potential partition of the sector competence field into sub-fields.

Throughout the rest of the paper the term 'node' (unless otherwise specified) identifies a non isolated node, and the term 'network' identifies a set of non-isolated nodes and the links between them.  $\{\hat{\mathbf{H}}, \mathbf{L}\}$  and  $\{\hat{\mathbf{H}}_w, \mathbf{L}_w\}$  are the networks formed by the non-isolated nodes in  $\{\mathbf{H}, \mathbf{L}\}$  and  $\{\mathbf{H}_w, \mathbf{L}_w\}$ , respectively<sup>13</sup>.

### 3.2 Exploration depth and collaboration incentives

The net contribution of ideas of a unit  $j$  to the R&D alliance with a unit  $i$  is conducive to higher expected innovation output only if  $i$  and  $j$  have a sufficiently large mutual understanding. We formalize this intuition by assuming perfect complementarity between novelty  $n_{ij}$  and overlap  $\lambda_{ij}$ . A partner's competence  $K_j$  is optimally exploited, when neither overlap nor novelty are redundant. The complementarity ratio  $\beta$  is higher, if  $i$  and  $j$  collaborate on a R&D project that is more incremental. On this ground, the form of R&D activity is here parametrized through the value of  $\beta$ , a higher  $\beta$  indicating a higher degree of exploration depth. The assumption that novelty and understanding are necessary inputs to collaboration is formalized by  $\beta \in [\beta_{\min}, \beta_{\max}]$ , with  $\beta_{\min} > 0$ , and  $\beta_{\max} < +\infty$ .

The collaboration link between  $i$  and  $j$  on a project of type  $\beta$  is written as  $ij_\beta$ . Conditional on the fact that  $j$  is prepared to collaborate with  $i$ ,  $i$ 's expected net pay-off from  $ij_\beta$  is:

$$\Pi_{ij}^\beta = \min\left(\frac{1}{\beta}\lambda_{ij}, n_{ij}\right) - \gamma(D_{ij}, \beta) \quad (5)$$

The term  $\min(\lambda_{ij}/\beta, n_{ij})$  is the normalized expected net<sup>14</sup> value of  $i$ 's benefit from joining alliance  $ij_\beta$ , gross of collaboration cost  $\gamma(D_{ij}, \beta)$ . This cost arises from the need to coordinate with  $j$ 's research routines and from knowledge-related transaction costs. A higher novelty ratio  $D_{ij}$  implies that unit  $i$  is familiar with a lower fraction of  $j$ 's knowledge repertoires, and spends more effort to coordinate with  $j$ 's activities. It is further assumed that the negotiation of binding collaboration agreements with one's partner is more costly if the outcomes of R&D are more uncertain. This is the case if R&D has greater breadth, that is, if  $\beta$  is lower. The function  $\gamma()$  takes the simple form

$$\gamma(D_{ij}, \beta) = \frac{1}{\beta}\phi + \eta D_{ij} \quad (6)$$

<sup>13</sup>Matlab simulations reported in Table 1 assume  $H = 300$ . In the simulation setting with  $W > 1$ ,  $\mathbf{H}$  is partitioned into  $W = 3$  communities of equal size  $H_w = 100$ .

<sup>14</sup>Net of the expected value of the same  $\beta$  project carried out in isolation.

where  $\eta > 0$ , and  $\phi > 0$  are fixed parameters. Using (3), one obtains

$$\Pi_{ij}^\beta = K_j \min\left(\frac{1}{\beta} p_{ij}, (1 - p_{ij})\right) - \frac{1}{\beta} \phi - \eta(1 - p_{ij}) \quad (7)$$

We assume that  $i$  makes a collaboration offer to  $j$  only if there is  $\beta \in [\beta_{\min}, \beta_{\max}]$ , such that  $\Pi_{ij}^\beta > 0$ . A R&D link  $ij$  is formed if and only if  $i$  makes a collaboration offer to  $j$  and the latter makes a collaboration offer to the former. This defines an R&D network as a pairwise equilibrium (Jackson and Wolinsky 1996) in the collaboration strategies of the agents (see appendix). For the sake of simplicity, we abstract from constraints on the number of alliances, which may result from capacity constraints (Goyal et al. 2006, Goyal and Vega-Redondo 2007, König et al. 2010, Caminati 2009).

To gain a better understanding on the working of the model, it is worth fixing a given  $\beta$  to consider the conditions under which  $\Pi_{ij}^\beta > 0$ . At any given  $K_j$ , the twin necessary conditions making collaboration  $ij_\beta$  attractive for  $i$  are:

$$K_j > k(\beta) = \phi + \eta + \left(\frac{1}{\beta}\right) \phi \quad (8)$$

$$\check{p}(K_j, \beta) < p_{ij} < \hat{p}(K_j, \beta) \quad (9)$$

At  $K_j > k(\beta)$  the collaboration interval is non empty; its lower and upper bounds are:

$$\check{p}(K_j, \beta) = \frac{\phi + \beta\eta}{K_j + \beta\eta} > 0 \quad (10)$$

$$\hat{p}(K_j, \beta) = \frac{K_j - \phi/\beta - \eta}{K_j - \eta} < 1 \quad (11)$$

Direct computation of the partial derivatives of (10), (11) provides an understanding of the conditions restricting the formation of alliances.

(i) An exogenous increase of the collaboration cost parameters  $\phi$  or  $\eta$  reduces the profitable collaboration opportunities: the width of the collaboration interval shrinks on both sides.

(ii) The width of the collaboration interval decreases and converges to zero as  $K_j$  converges to  $k(\beta)$  from above.

(iii) A change  $\Delta\beta > 0$  towards a more incremental form of R&D causes a rightward shift of the collaboration interval, which means that the minimum proximity requirement becomes more restrictive, and the maximum proximity requirement more slack.

Growing knowledge complexity increases the collaboration cost. On this ground, the parameters  $\phi$  and  $\eta$  are tuned, in the long-run, with the knowledge parameter  $\Psi$ . They are restricted in a parameter region  $\Gamma$  (see appendix), such that the distance between the expected endowment size  $\frac{1}{2}\Psi$  and the knowledge threshold  $k(\beta = 1) = 2\phi + \eta$  is neither too large or too small. The intuition behind this restriction is clear. Observing that  $k(\beta)$  is a strictly decreasing function of  $\beta$ , the restriction implies that if and only if sufficiently incremental R&D projects are in focus, that is,  $\beta > \beta_\phi$ , then some agents in the economy

meet the knowledge constraint (8). The critical threshold  $\beta_\phi$  increases with  $\phi$  (see appendix).

## 4 Results

This section presents the main results of the paper. A first set of propositions is concerned with the multi-sector and one-sector R&D networks, and the comparative-static effects of variations in the collaboration cost (simulations in table 1). A second set of predictions is concerned with the forces producing endogenous changes in link formation.

### 4.1 Collaboration cost and R&D network structure

The selection by any unit  $i$  of its potential R&D partners obeys the constraints (8) and (9). The former amounts to a selection by the size of the knowledge endowment, the latter to a selection by similarity in the composition of knowledge. The derivative  $\partial k(\beta)/\partial \beta < 0$  shows that (8) restricts alliance formation to sufficiently incremental projects. In view of (9), this type of alliances is conditional on a relatively high similarity in the composition of the knowledge base. In the context of a multisector network, a disproportionately large fraction of  $i$ 's collaboration offers is therefore addressed to units operating in  $i$ 's sector of activity. The remark clarifies the intuition behind the following results:

**Proposition 1** *If the set of agents is partitioned into a larger number  $W$  of competence communities, leaving other parameters unchanged: (i) a lower number of alliances is formed, and the ratio  $\rho$  between network average degree and size is lower; (ii) modularity is higher; (iii) the transitivity ratio  $C_N/C_N^R$  is also higher.*

The simulation outcomes of table 1 illustrate the above statements by comparing network properties at  $W = 3$ , and  $W = 1$ . The result concerning the transitivity ratio  $C_N/C_N^R$  may deserve further clarification. The existence of a sufficiently high minimum proximity ratio contributes to transitivity: if  $i$  and  $j$  collaborate with the same  $h$ , the composition of their endowments  $\mathbf{A}_i$  and  $\mathbf{A}_j$  is, on average, more similar than if they were picked up at random from  $\hat{\mathbf{H}}$ . This selection by composition of knowledge implies that the direct collaboration between any two neighbors of a third unit is more frequent than it would be if the wiring connections was random. In an R&D network, the global clustering coefficient  $C_N$  is therefore higher than  $C_N^R$ . This selection effect is stronger in a pooled than in a non-pooled network because the average knowledge overlap is lower in the former. Stronger selection by knowledge composition preserves transitivity in the pooled network, in spite of the much lower ratio between average degree and size.<sup>15</sup> This explains why the ratio  $C_N/C_N^R$  is definitely higher at  $W > 1$  than at  $W = 1$  (table 1).

<sup>15</sup>Lower density of connections triggers a fall of transitivity, if the wiring of connections is random.

In an R&D network pooling a large number  $W$  of sector-networks, sufficiently sparse (but non-vanishing) cross-sector connections produce low  $\rho$ , high modularity, high transitivity ratio  $C_N/C_N^R$ , and low average path length<sup>16</sup> The combination of these characters gives rise to the small-world property. This argument is corroborated by the evidence that the small-world ratio is systematically far higher in a pooled network than in any of its sector networks (Tomasello et al. 2013, table 7).

The modularity of a multi-sector R&D network has the further implication that the high-degree and low-degree nodes form a disproportionately large fraction of their links within their group. The effect is stronger if the collaboration cost parameter  $\phi$  is higher.

**Proposition 2** *Assortativity by degree is positive in a pooled R&D network, and for a large enough  $\phi$ , it is higher than in a sector network, or a non-pooled network of identical size (table 1).*

In a modular multi-sector network a disproportionately large fraction of links connect nodes belonging in the same sector. Sufficient variation of community size  $\hat{H}_w$  across the sectors  $w = 1, \dots, W$  produces positive correlation between sector average degree and size. This implies that the frequency with which two high-degree nodes belong in the same sector, and the frequency with which they are connected, is higher than a random wiring of connections would suggest. Positive assortativity by degree in the pooled network is a consequence.<sup>17</sup>

The above proposition is consistent with the empirical evidence concerning the different assortativity properties of multisector and sector R&D networks<sup>18</sup>. The explanation differs from other explanations based on network growth<sup>19</sup>; it is corroborated by the data showing that, in each four-year period between 1986 and 2009, network average degree and size are positively correlated across the sector networks in manufacturing and services (table 2).

The model yields the further prediction that the cross field collaborations are more vulnerable to a rise of the collaboration cost parameters  $\phi$  and  $\eta$ . Ceteris paribus, a higher value of the latter makes novelty more costly; a higher value of the former makes all collaborations less rewarding, but the lower  $\beta$ , the stronger is the effect in question.

**Proposition 3** *Lower collaboration cost parameters  $\phi, \eta$  produce a more dense R&D network, and a change of its architecture, caused by a larger proportion of*

<sup>16</sup>The average path length is the shortest relational distance between a node and every other, averaged over all nodes in  $\hat{\mathbf{H}}$ . Average path length is low relative to a random network of a corresponding size and average degree.

<sup>17</sup>Table 1 reveals that a second weaker source of positive assortativity by degree is positive assortativity by  $K$ , and positive correlation between  $K_i$  and degree  $d_i$ .

<sup>18</sup>Tomasello et al. (2013) suggests that assortativity by degree is positive in the pooled networks, and mostly negative in the sector networks.

<sup>19</sup>Explanations based on network-growth either assume a preferential attachment for the most central units in the network (which yields a disassortative network, Ramasco et al. 2004), or add capacity constraints to preferential attachment (which yields a transition to positive assortativity by degree, König et al. 2010).

high-breadth projects, and a corresponding fall of the fraction  $\chi$  of within-sector collaborations in the total. This tends to consolidate the network into a lower number of disconnected components and may produce a single giant component (table 1).

The diffusion of information and communication technologies (ICT) since the mid 1980s tilted downward the (information and transaction) costs of R&D collaboration, especially in fields of activity where innovation bears closer roots in abstract and codifiable knowledge. One is led to conjecture that this contributed to the growing phase of sector and cross-sector R&D alliance in the following decade.

## 4.2 Endogenous drivers of change

The pattern of R&D coalitions at time  $t$  affects knowledge accumulation through innovation and knowledge spillovers. The following remarks assume a simplified framework in which the absorption of external ideas takes place through interaction with direct partners. Knowledge spillovers through indirect links do not materialize in the unit time interval.

Any new idea produced by the alliance  $ij$  extends the knowledge overlap  $\lambda_{ij}$ . Stronger convergence between the stocks  $A_i$ ,  $A_j$  is produced by the spillover of ideas between  $i$  and  $j$ ;  $\lambda_{ij}$  grows in this case at the loss of novelty  $n_{ij}$ ,  $n_{ji}$ . The time persistence of a link  $ij$  depends on a weighing of the knowledge convergence effects produced by direct collaboration with the potential novelty-preserving effects of  $i$ 's and  $j$ 's simultaneous links with other units (R&D carried out in isolation is neglected). Weighing of convergence and divergence is dependent on the local topology of the network.

If a unit  $j$  does not have any R&D partner other than  $i$ , nothing can prevent the eventual loss of novelty  $n_{ij}$ ;  $p_{ij}$  converges to 1, and collaboration  $ij$  is eventually unattractive for  $i$ .

**Proposition 4** *A link  $ij$  is unpersistent, if  $i$  or  $j$  has degree  $d = 1$ . As a corollary, a star R&D network is unstable.*

The proposition implies that any persistent R&D network architecture does not have paths ending with a terminal node, or, equivalently, that each node has at least two links.

A more general formulation of the sufficient conditions for knowledge convergence between direct partners can be expressed through the *neighbor overlap ratio*  $\varsigma_{ij}$  of a node  $j$  relative to a node  $i$ : this is the fraction of  $j$ 's neighbors that are  $i$ 's neighbors.<sup>20</sup> If  $\varsigma_{ij}$  is maximal,  $j$  does not have novelty sources outside  $ij$  that are not promptly in the reach of  $i$ .<sup>21</sup> This suggests that, if  $\varsigma_{ij}$  is maximal,

<sup>20</sup>If  $ij$  is a link, then  $0 \leq \varsigma_{ij} \leq (d_j - 1)/d_j$ .

<sup>21</sup>The innovation flow produced in one period by  $j$ 's alliances other than  $ij$  will be ready for absorption by partner  $i$  only in the next. This flow feeds the novelty  $n_{ij}$ , but it can not prevent the eventual fall of the novelty ratio  $D_{ij}$ , because the flow will be eventually negligible relative to the stock  $K_j$ , unless the innovation rate persistently accelerates through time. This persistent acceleration is ruled out in the text.



the eventual rise of the proximity ratio  $p_{ij}$  above the critical level (11) cannot be avoided.

A specular case is that in which the instability of the link  $ij$  is produced by the knowledge divergence of  $j$  relative to  $i$ . If  $\varsigma_{ij} = \varsigma_{ji} = 0$ , the short-run fall of the proximity ratio  $p_{ij}$  cannot be avoided, if the number  $d_j$  of  $j$ 's alliances is large enough.

The network topology in figure 1 illustrates these two sources of instability. Knowledge convergence is bound to produce the eventual severance of all links other than  $hj$ . The same topology embeds a potential source of instability through *short-run* knowledge divergence, provided that  $d_h$  is large enough.

The relevance of the arguments above is clarified by the observation that a pooled R&D network is nearly decomposable into clusters of nodes featuring a high frequency of triangles (closed paths of length 2). If, in any of these triangles, there is a vertex with degree 2, the node in question has a maximal *neighbor overlap ratio*, hence it lacks the sources of novelty which are necessary to the persistence of its links.

More generally, the proposition lends qualified support to the conclusion that sufficiently high network transitivity favors knowledge convergence between participants. Qualification is necessary, because, in a modular pooled network, with a sufficiently high fraction  $\chi$  of within-sector links in the total, knowledge convergence within the sectors may be associated with knowledge divergence across the sectors, leading to module segregation. If the severance of cross-field collaborations produces segregated network components, loss of external sources of novelty and decay of radical innovations are a consequence. With a stationary, or too slowly expanding, search space, the aggregate innovation flow is eventually bound to fall, and this accelerates knowledge convergence within the competence communities, producing a further shift towards more incremental forms of R&D. This way, the process is self-reinforcing.

## 5 Discussion

Specialization of competences is a cause and effect of the growing complexity of knowledge. The formation of R&D alliances is conditioned by the pattern of specialization into competence communities, and by the varying opportunity to exploit the knowledge similarity between partners, in relation with the breadth/depth of the R&D.

A network linking organizations from a multiplicity of competence communities has a transitive pattern of connections, and is modular. The larger the number of communities, the higher the modularity. The model results are coherent with the interpretation that modularity is the way in which the small-world properties are embedded in a large-scale R&D network. Supporting evidence on the relevance of such properties comes from the finding (Shilling and Phelps 2007) that high clustering and low average path length of network relations are positively correlated with innovation output. Small-world structures implement a combination of fast access to novel information, with the capacity to preserve

novelty through time (Uzzi and Spiro 2005, Uzzi et al. 2007). We argue that this capacity is typically carried by alliances on more radical R&D projects, and crossing the boundaries of competence communities.

This paper brings into focus the changes in R&D-network structure that are induced by different scales of aggregation. The focus on competence communities contributes to clarifying why a real-world multi-sector R&D network combines high clustering with positive assortativity by degree. Such properties are the markers of structural similarity with respect to a typical socio-economic network (Newman and Park 2003). Remarkably, the same structural similarity partly fails at the sector level. Tomasello et al. (2013) shows that the propensity of the high-degree nodes to connect with other high-degree nodes has a sign reversal between multi-sector and sector networks. The sign reversal does not show up (with one exception) in table 1, a finding that is *prima-facie* consistent with the abstract remark that, in a multi-layer structure, the difference between pooled and non-pooled is a difference in degree, not in kind: a sector community is itself pooled if it hosts a sufficiently large number of more specialized sub-communities. This condition is fulfilled in our artificial economy if the random assignment of ideas causes 'sufficient' knowledge heterogeneity in a sector. One is led to conjecture that the sign reversal in degree-assortativity shown by Tomasello et al. (2013) is explained by missing knowledge heterogeneity in the (SIC three-digits codes) real-world sector networks.

The complementarity of novelty and common understanding in R&D collaboration produces bounds to the incentive-compatible knowledge proximity between partners. This implies that local processes of knowledge convergence and divergence trigger changing collaboration incentives and are a potential source of instability<sup>22</sup>. This remark is pinned down in this paper to a class of network architectures, including the star network. An insight is that the star network may not occupy, in the context of R&D alliances, the same focal position occupied in other socio-economic contexts (Goyal and Vega-Redondo 2007).

Studies highlighting the falling phase of R&D alliance after 1997 agree on the interpretation that the reduced incentive to alliance formation may be explained by greater homogeneity of the competence bases, produced by collaboration (Tomasello et al. 2013, Gulati et al. 2012). The twist in network organization after the late 1990's in biotechnology, multi-media and other industries is interpreted by Gilsing and Nooteboom (2006), Gilsing and Duysters (2008) as a shift towards a more exploitation-centered phase of R&D collaboration, leading to a more fragmented network.

While broadly consistent with these interpretations, section 4.2 makes the point that a causal factor of R&D-network evolution is the fraction  $\chi$  of within-field collaborations in the total. A high  $\chi$  reflects the high cost of cross-sector alliances agreed on more radical R&D projects. If  $\chi$  is sufficiently large, there

---

<sup>22</sup>A similar approach is in Cowan and Jonard (2009), Baum et al. (2014). If the complementarity between novelty and common understanding is neglected, the recombinant-knowledge explanation of R&D networks does not carry the same stability implications (König et al. 2012).

is a low probability that two partners joined by a cross-sector link have other partners in common. This makes the link fragile, that is, liable to be destroyed by knowledge divergence. A high  $\chi$  is a potential source of a further increase in  $\chi$ , which may reflect network disintegration into separate competence communities. Segregation of the network components brings with it a lower breadth of R&D activity, thus accelerating knowledge convergence within the components, and the long-run decline of innovation. Eventual decay of R&D collaboration in the sector networks is a consequence<sup>23</sup>.

## 6 Conclusion

The results of this paper are strictly tied to a combination of assumptions, jointly distinguishing this from other approaches to R&D network formation.

The set of R&D organizations is partitioned into a multiplicity of heterogeneous competence communities, defined by the distribution of the knowledge stocks. The size and composition of these stocks affect the choice to collaborate on R&D projects extending along the dimensions of exploration depth and breadth. Full abstraction is made from trust considerations, and from indirect knowledge spillovers, with the implication that one's choice of R&D partners is independent of the pattern of alliances produced by the antecedent process of network growth. This simplification enables a closer scrutiny of the knowledge complementarities conditioning the formation of pairwise R&D alliances.

The properties of clustering, modularity, small-world, and degree-assortativity of empirical R&D networks are recovered from this approach. The results throw further light on the interpretation of such properties, in particular on the explanatory power of modularity, and the reasons why a large multi-sector R&D network is similar to a characteristic social network.

The paper suggests that link instability is triggered by topological patterns of alliance causing knowledge convergence or divergence between partners. To the extent that the R&D network in one industry is a functional and organizational module of a larger multi-sector network, the evolution of the latter interacts with the evolution of the former: network stability is best addressed at the mutisector scale of analysis.

The present line of argument is complementary with other approaches focused on social-capital, network-wide knowledge spillovers, industry market structure, or tacit knowledge. Integration of the different lines of argument demands a complex theoretical framework, extending its domain to forms of heterogeneity going well beyond the codifiable dimensions of knowledge<sup>24</sup>.

## Appendix

<sup>23</sup>The insight is not inconsistent with the interpretations suggesting an inherent tendency of R&D networks to a cyclical pattern of evolution (Callon 2002, Nooteboom 2000a, Gilsing and Nooteboom 2006).

<sup>24</sup>Agent based models of R&D network formation are a promising line of research (Tedeschi et al. 2014, Llerena and Ozman 2012).

## Section 2

*Modularity:* For a given network  $\{\mathbf{H}, \mathbf{L}\}$ , with adjacency matrix  $\mathbf{G} : H \times H$ , such that  $G_{ij} = G_{ji} = 1$ , if  $ij \in \mathbf{L}$ ,  $G_{ij} = G_{ji} = 0$  otherwise, the modularity of a partition  $\{\mathbf{H}_1, \dots, \mathbf{H}_W\}$  is

$$Q = \frac{1}{T} \sum_{ij} \left( G_{ij} - \frac{d_i d_j}{T} \right) \delta(c_i, c_j)$$

where  $d_i$  is the degree (number of links) of node  $i$ ;  $T = \sum_i d_i = 2 \cdot \#\mathbf{L} = \sum_{ij} G_{ij}$ ; for  $i \in \mathbf{H}$ ,  $c_i = w \in \{1, \dots, W\}$ , such that  $i \in \mathbf{H}_w$ ;  $\delta(w, z)$  is the Kronecker delta, with  $\delta(w, z) = 1$  if  $w = z$ , and  $\delta(w, z) = 0$  otherwise. The modularity of  $\{\mathbf{H}, \mathbf{L}\}$  is the  $Q$  value produced by the  $Q$ -maximizing partition of  $\mathbf{H}$  (Newman and Girvan 2002, 2004; Newman 2006, 2010, p. 375).

*Small world:* A network  $\{\hat{\mathbf{H}}, \mathbf{L}\}$  is said to be a small world if: (i) the ratio  $\rho$  of network average degree to network size is sufficiently low; (ii) the ratio  $C/PL$  between the average local clustering coefficient  $C = E_{i \in \hat{\mathbf{H}}} (C_i)$  and the average path length  $PL$  (the shortest relational distance between a node and every other, averaged over all nodes in  $\hat{\mathbf{H}}$ ) is higher than the ratio  $C_R/PL_R$  found in random networks of corresponding size and average degree (Watts and Strogatz 1998).

*Assortativity:* A network is positively assortative according to the (scalar) characteristic  $c$ , if the nodes that are more similar with respect to  $c$ , have a higher than expected frequency of connection. Network assortativity is measured by

$$r = \frac{\sum_{ij} (\mathbf{G}_{ij} - d_i d_j / T) c_i c_j}{\sum_{ij} (d_i \delta(i, j) - d_i d_j / T) c_i c_j} \quad (12)$$

where  $c_i$  is the value of  $c$  in node  $i$  (Newman 2010, p. 229). Assortativity by degree is obtained by replacing  $c_i$  and  $c_j$  with  $d_i$  and  $d_j$ , respectively.

### Section 3.1

Every unit  $i \in \mathbf{H}_w$  is randomly assigned each of the  $\Psi$  known ideas in its competence field  $\mathbf{X}_w$  with probability  $\frac{1}{2}$ .  $K_i$  is the number of ideas in  $i$ 's knowledge endowment  $\mathbf{A}_i$ . The probability of  $K_i = s$  is  $\binom{\Psi}{s} (1/2)^\Psi$ , and the expected size of  $K_i$  is:

$$E(K_i) = \sum_{s=1}^{s=\Psi} [s \binom{\Psi}{s} (1/2)^\Psi] = \frac{1}{2} \Psi$$

It is assumed that the resulting allocation of ideas is representative. For a given  $W \geq 1$ , and a exogenous partition  $\{\mathbf{H}_1, \dots, \mathbf{H}_W\}$  of  $\mathbf{H}$ , a induced allocation  $\mathbf{A}$  is representative if: (1) the number  $\Psi$  and the community size  $H_w = \#\mathbf{H}_w$  are sufficiently large that the community-average endowment size

$$\frac{1}{H_w} \sum_{i \in \mathbf{H}_w} K_i$$

is sufficiently close to  $\frac{1}{2}\Psi$ , and the variance of  $K_i$  is sufficiently low; (2) for any  $i \in \mathbf{H}_{w^\circ}$ , and  $w \neq w^\circ$ , the difference

$$E_{j \in \mathbf{H}_{w^\circ}}(p_{ij}) - E_{j \in \mathbf{H}_w}(p_{ij})$$

is positive and sufficiently large.

### Section 3.2

*Pairwise equilibrium of collaboration strategies:* Given a representative allocation of ideas  $\{\mathbf{A}_i\}_{i \in \mathbf{H}}$ , let  $\mathbf{B}_{ij} = \{\beta \in (\beta_{\min}, \beta_{\max}) | \Pi_{ij}^\beta > 0\}$ . A collaboration strategy of unit  $i$  is a choice  $\mathbf{S}_i = \{e_{i1}, \dots, e_{iH}\}$ , such that  $e_{ij} \in \{0, 1\}$ , and  $e_{ij} = 1$  only if  $\mathbf{B}_{ij} \neq \emptyset$ . A pairwise equilibrium (Jackson and Wolinsky, 1996) is a strategy profile  $\mathbf{S}^* = \{\mathbf{S}_1^*, \dots, \mathbf{S}_H^*\}$ , such that, for any  $j \neq i$ ,  $e_{ij} = 1$  implies  $e_{ji} = 1$ , and  $\mathbf{S}^*$  is robust to the formation of two-agents coalitions: for every  $i$  and  $j$  in  $\mathbf{H}$ , such that  $0 = e_{ij} \in \mathbf{S}_i^*$ ,  $0 = e_{ji} \in \mathbf{S}_j^*$ , there is no strategy pair  $(\mathbf{S}'_i, \mathbf{S}'_j)$  such that  $1 = e_{ij} \in \mathbf{S}'_i$ ,  $1 = e_{ji} \in \mathbf{S}'_j$ , and  $\mathbf{B}_{ij} \cap \mathbf{B}_{ji} \neq \emptyset$ .

*Region of collaboration cost parameters:*  $\phi$  and  $\eta$  are restricted to a two-dimensional bounded parameter region  $\Gamma$ , defined by a maximum distance  $\bar{R}$  between the expected endowment size  $\frac{1}{2}\Psi$  and the knowledge threshold  $k(\beta)$  resulting from the restriction  $\beta = 1$  in (8). For a fixed choice of  $\Psi$ ,  $\bar{R}$ , and  $\bar{\phi}$ , the parameter region  $\Gamma$  is defined by:

$$1 \leq \phi \leq \bar{\phi}, \quad \frac{1}{2}\Psi - \bar{R} \leq 2\phi + \eta \leq \frac{1}{2}\Psi + \bar{R} \quad (13)$$

(13) implies  $\eta_{\min} = \frac{1}{2}\Psi - \bar{R} - 2\bar{\phi}$ ,  $\eta_{\max} = \frac{1}{2}\Psi + \bar{R} - 2$ ; any  $\eta \in [\eta_{\min}, \eta_{\max}]$  defines  $\phi_{\min}(\eta) = (\frac{1}{2}\Psi - \bar{R} - \eta)/2$ ,  $\phi_{\max}(\eta) = \min\{(\frac{1}{2}\Psi + \bar{R} - \eta)/2, \bar{\phi}\}$ . In our simulations we fix  $\Psi = 100$ ,  $\bar{R} = 6$ , and  $\bar{\phi} = 9$ .

*Definition of  $\beta_\phi$ :* Let  $K_{\max} = \max(K_i | i \in \mathbf{H})$ .  $\beta_\phi$  is defined by  $K_{\max} = k(\beta_\phi)$ ; direct computation yields  $\beta_\phi = \phi / (K_{\max} - \phi - \eta)$ . For any  $(\phi, \eta) \in \Gamma$ , if  $\beta \leq \beta_\phi$ , then  $K_i \leq k(\beta)$  all  $i \in \mathbf{H}$ .

### References

- Ahuja C (2000) Collaboration networks, structural holes, and innovation: A longitudinal study. *Admin Sci Quart* 45:425-455
- Antonelli C, Krafft J, Quatraro F (2010) Recombinant knowledge and growth: the case of ICTs. *Structural Change and Economic Dynamics* 21:50-69
- Arora A, Ganbardella A (1994) The changing technology of technological change: general and abstract knowledge and the division of innovative labour. *Res Policy* 23:523-532
- Arora A, Ganbardella A (2010) Ideas for rent: an overview of markets for technology. *Ind Corp Change* 19:775-803
- Baum JAC, Shipilov AV, Rowley TJ (2003) Where do small worlds come from? *Ind Corp Change* 12:697-725
- Baum JAC, Cowan R, Jonard N (2014) Network-independent partner selection and the evolution of innovation networks. *Manage Sci* 56:2094-2110

- Bogenrieder I, Nooteboom B (2004) The emergence of learning communities: A theoretical analysis. In: Tsoukas H, Mylonopoulos N (eds) *Organizations as knowledge systems*. Palgrave Macmillan, New York, pp 46-66
- Breschi S, Lissoni F, Malerba F (2003) Knowledge relatedness in firm technological diversification. *Res Policy* 32:69-87
- Burt RS (1992): *Structural Holes. The social structure of competition*. Harvard University Press, Cambridge, MA
- Caldarelli G (2007) *Scale-Free Networks. Complex webs in nature and technology*. Oxford University Press, Oxford
- Callon M (2002) From science as an economic activity to socioeconomics of scientific research. The dynamics of emergent and consolidated techno-economic networks. In: Mirowski PP, Sent EM (eds) *Science bought and sold: Essays in the economics of science*. University of Chicago Press, Chicago, pp 277-317
- Caminati M (2006) Knowledge growth, complexity, and the returns to R&D. *J Evol Econ* 16:207-229
- Caminati M (2009) A knowledge based approach to collaboration in basic research. MPRA Paper n° 19521, <http://mpa.ub.uni-muenchen.de/19521/>
- Cantner U, Graf H (2006) The network of innovators in Jena: An application of social network analysis. *Res Policy* 35:463-480
- Cloodt M, Hagedoorn J, Roijakkers N (2006) Trends and patterns in interfirm R&D networks in the global computer industry: An analysis of major developments, 1970-1999. *Bus Hist Rev* 80:725-746
- Cohen WM, Levinthal DA (1990) Absorptive capacity: A new perspective on learning and innovation. *Admin Sci Quart* 35:128-152
- Cowan R, Jonard N, Zimmerman JB (2006) Evolving network of inventors. *J Evol Econ* 16: 155-174
- Cowan R, Jonard N (2009) Knowledge portfolios and the organization of innovation networks. *Acad Manage Rev* 34:320-342
- Dawid H, Hellmann T (2014) The evolution of R&D networks. *J Econ Behav Organ* 105:158-172
- Egbetokun A, Savin I (2014) Absorptive capacity and innovation: when is it better to cooperate? *J Evol Econ* 24:399-420
- Fleming L, King C, Juda AI (2007) Small worlds and regional innovation. *Organ Sci* 18:938-954
- Fleming L, Marx M (2006) Managing creativity in small worlds. *Calif Manage Rev* 48:6-27
- Fleming L, Sorenson O (2001) Technology as a complex adaptive system: evidence from patent data. *Res Policy* 30:1019-1039
- Frenken K (2006) Technological innovation and complexity theory. *Economics of Innovation and New Technology* 15:137-155
- Frenken K, Marengo L, Valente M (1999) Interdependencies, nearly-decomposability and adaptation. In: Brenner T (ed) *Computational Techniques for Modelling Learning in Economics*. Kluwer, Dordrecht, pp 145-165
- Frenken K, Nuvolari A (2004) Entropy statistics as a framework to analyse technological evolution. In: Foster J, Hözl W (eds) *Applied evolutionary eco-*

nomics and complex systems. Edward Elgar Publishing, Cheltenham, UK and Northampton, MA, pp 95-132

Gilsing V, Duysters GM. (2008) Understanding novelty creation in exploration networks. Structural and relational embeddedness jointly considered. *Technovation* 28:693-708

Gilsing V, Nooteboom B (2006) Exploration and exploitation in innovation systems: The case of pharmaceutical biotechnology. *Res Policy* 35:1-23

Goyal S (2007) *Connections. An Introduction to the economics of networks.* Princeton University Press, Princeton

Goyal S, Joshi S (2003) Networks of collaboration in oligopoly. *Game Econ Behav* 43:57-85

Goyal S Joshi S (2006) Unequal connections. *Int J Game Theory* 34:319-349

Goyal S, Moraga-González JL (2001) R&D networks. *RAND J Econ* 32:686-707

Goyal S, van der Leij M, Moraga JL (2006) Economics: emerging small world. *J Polit Econ* 114:403-412

Goyal S, Vega-Redondo F (2007) Structural holes in social networks. *J EconTheory* 137:460-92

Gulati R (1995) Social structure and alliance formation patterns: A longitudinal analysis. *Admin Sci Quart* 40:619-652

Gulati R, Gargiulo M (1999) Where do inter-organizational networks come from? *Am J Sociol* 91:481-510

Gulati R, Sytch M, and Tatarynowicz A (2012) The rise and fall of small worlds: Exploring the dynamics of social structure. *Organ Sci* 23:449-471

Jackson MO (2008) *Social and Economic Networks.* Princeton University Press, Princeton

Jackson MO, Wolinsky A (1996) A strategic model of social and economic networks. *J Econ Theory* 71:44-74

Hansen MT (2002) Knowledge networks: Explaining effective knowledge sharing in multiunit companies. *Organ Sci* 13:232-250

Hagedoorn J (2002) Inter-firm R&D partnership: an overview of major trends and patterns since 1960. *Res Policy* 31:477-492

Hanaki N, Nakaijima R, Ogura Y (2010) The dynamics of R&D network in the IT industry. *Res Policy* 39:386-399

Holland JH (1992) *Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, artificial intelligence,* 2nd edn. MIT Press, Cambridge MA

Kauffman S (1988) The evolution of economic webs. In: Anderson PW, Arrow KJ, Pines D (eds) *The Economy as an evolving complex system.* Addison-Wesley, Reading MA, pp 125-146

Kauffman S, Lobo J, Macready WG (2000) Optimal search on a technology landscape. *J Econ Behav Organ* 43:141-166

König MD, Tessone JC, Zenou Y (2010) From assortative to disassortative networks: The role of capacity constraints. *Advances in Complex Systems* 13:483-499

- König MD, Battiston S, Napoletano M, Schweitzer F (2011) Recombinant knowledge and the evolution of innovation networks. *J Econ Behav Organ* 79:145-164
- König MD, Battiston S, Napoletano M, Schweitzer F (2012) The efficiency and stability of R&D networks. *Game Econ Behav* 75:694-713
- Krafft J, Quatraro F, Saviotti PP (2011) The knowledge base evolution in biotechnology: a social network analysis. *Economics of Innovation and New Technology* 20:445-475
- Krafft J, Quatraro F, Saviotti PP (2014) Knowledge characteristics and the dynamics of technological alliances in pharmaceuticals: empirical evidence from Europe, US and Japan. *J Evol Econ* 24:587-622
- Lane D, Malerba F, Maxfield R, Orsenigo L (1996) Choice and action. *J Evol Econ* 6:43-76.
- Llerena P, Ozman M (2013) Networks, irreversibility, and knowledge creation. *J Evol Econ* 23:431-453
- March J (1991) Exploration and exploitation in organizational learning. *Organ Sci* 2:71-87
- Marengo L, Pasquali C, Valente M (2005) Decomposability and modularity of economic interactions. In: Callebaut W, Rasskin-Gutman D (eds) *Modularity. Understanding the development and evolution of natural complex systems*. MIT Press, Cambridge MA pp 383-408
- Mowery DC, Oxley JE, Silverman BS (1998) Technological overlap and interfirm cooperation: Implications for the resource-based view of the firm. *Res Policy* 27:507-523
- Nesta L, Saviotti PP (2005) Coherence of the knowledge base and the firm's innovative performance: evidence from the US pharmaceutical industry. *J Ind Econ* 53:123-42
- Newman MEJ (2006) Modularity and community structure in networks. *P Natl Acad Sci USA* 103:8577-8582
- Newman MEJ (2010) *Networks. An introduction*. Oxford University Press, New York
- Newman MEJ, Girvan M (2002) Community structure in social and biological networks. *P Natl Acad Sci USA* 99:7821-7826
- Newman MEJ, Girvan M (2004) Finding and evaluating community structure in networks. *Phys Rev E* 69:026113
- Newman MEJ, Park J (2003) Why social networks are different from other types of networks. *Phys Rev E* 68:036122
- Nooteboom B (1992) Toward a dynamic theory of transactions. *J Evol Econ* 2:281-299
- Nooteboom B (1999): *Inter-firm alliances: Analysis and design*, Routledge, London
- Nooteboom B (2000a) *Learning and innovation in organization and economies*. Oxford University Press, Oxford
- Nooteboom B (2000b) Learning by interaction: absorptive capacity, cognitive distance and governance. *Journal of Management and Governance* 4: 69-92



- Nooteboom B (2004) Inter-firm collaboration, learning and networks. Routledge, London
- Nooteboom B, Haverbeke WV, Duysters G, Gilsing V, van den Oord A (2007) Optimal cognitive distance and absorptive capacity. *Res Policy* 36:1016-1034
- Orsenigo L (2006) Clusters and clustering in biotechnology: stylised facts, issues and theories. In: Braunerhjelm P, Feldman MP (eds) *Cluster genesis*. Oxford University Press, Oxford UK, pp195-218
- Orsenigo L, Pammolli F, Riccaboni M (2001) Technological change and network dynamics. Lessons from the pharmaceutical industry. *Res Policy* 30: 485-508
- Oxley JE (1997) Appropriability hazards and governance in strategic alliances: A transaction-cost approach. *J Law Econ Organ* 13:387-409
- Powell WW, Koput KW, Smith-Doerr L (1996) Interorganizational cooperation and the locus of innovation: Networks of learning in biotechnology. *Admin Sci Quart* 41:116-145
- Powell WW, White DR, Koput KW, Owen-Smith J (2005) Network dynamics and field evolution: the growth of interorganizational collaboration in the life-sciences. *Am J Sociol* 110:1132-1205
- Reiter S. (2001) Knowledge, discovery and growth. In: Olson GM, Malone TW, Smith JB (eds) *Coordination theory and collaboration technology*. Lawrence Erlbaum Associates, Mahwah, NJ, pp 193-260
- Roijakkers N, Hagedoorn J (2006) Inter-firm R&D partnering in pharmaceutical biotechnology since 1975: Trends, patterns and networks. *Res Policy* 35:431-446
- Rosenkopf L, Schilling MA (2007) Comparing alliance network structure across industries: observations and explanations. *Strategic Entrepreneurship Journal* 1:191-209
- Rosenkopf L, Schilling MA (2012) Correction to Comparing alliance network structure across industries: observations and explanations. *Strategic Entrepreneurship Journal* 6:200-202
- Saviotti PP (1988) Information, variety and entropy in technoeconomic development. *Res Policy* 17:89-103
- Saviotti PP (2009) Knowledge networks: structure and dynamics. In: Pyka A, Scharnhorst A (eds), *Innovation networks*. Springer-Verlag, Berlin, Heidelberg, pp 19-41
- Shilling MA, Phelps CC (2007) Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. *Manage Sci* 53:1113-1126
- Simon HA (2005) The architecture of complexity in an evolving world: The role of near decomposability. In: Callebaut W, Rasskin-Gutman D (eds) *Modularity. Understanding the development and evolution of natural complex systems*. MIT Press, Cambridge MA, pp ix-xiii
- Tedeschi G, Vitali S, Gallegati M (2014) The dynamic of innovation networks: a switching model on technological change, *J Evol Econ* 24: 817-834
- Tomasello MV, Napoletano M, Garas A, Schweitzer F (2013) The rise and fall

of R&D networks. *ofce* WP 2013-15 <http://www.ofce.sciences-po.fr/pdf/dtravail/WP2013-15.pdf>

Uzzi B, Spiro J (2005) Collaboration and creativity: The small world problem. *Am J Sociol* 111:447-504

Uzzi B, Amaral LA, Reed-Tsochas F (2007) Small-world networks and management science research: a review. *European Management Review* 4:77-91

Vega-Redondo F (2007) *Complex Social Networks*. Cambridge University Press, Cambridge UK

Walker G, Kogut B, Shan W (1997) Social capital, structural holes and the formation of an industry network. *Organ Sci* 8:109-125

Watts DJ (1999) *Small Worlds*. Princeton University Press, Princeton

Watts DJ, Strogatz SH (1998) Collective dynamics of small-world networks. *Nature* 393: 440-442

Weitzman ML (1998) Recombinant Growth. *Q J Econ* 113:331-360

Wu J, Shanley MT (2009) Knowledge stock, exploration, and innovation: Research on the United States electromedical industry. *J Bus Res* 62:474-83

Wuyts S, Colombo MG, Dutta S, Nooteboom B (2006) Empirical tests of optimal cognitive distance. *J Econ Behav Organ* 58:277-302

**Table 1.a**  $\eta = 46$ 

	$W = 3, \text{ pooled}$			$W = 3, \text{ sector}^{wa}$			$W = 1$		
	$\phi_{min}$	$\phi_{mean}$	$\phi_{max}$	$\phi_{min}$	$\phi_{mean}$	$\phi_{max}$	$\phi_{min}$	$\phi_{mean}$	$\phi_{max}$
<i>size</i>	210	140	72	70 <sup>a</sup>	46.7 <sup>a</sup>	24 <sup>a</sup>	205	128	54
$\rho$	0.48	0.25	0.18	0.81	0.68	0.52	0.80	0.59	0.45
$\chi$	0.56	0.92	1	1	1	1	1	1	1
<i>components</i>	1	1	3	1	1	1	1	1	1
$Q$	0.24	0.58	0.60	0.011	0.031	0.069	0.013	0.028	0.091
$C_N$	0.78	0.79	0.83	0.98	0.89	0.83	0.97	0.89	0.79
$C_N / C_N^R$	1.2	2.51	3.10	1.05	1.09	1.24	1.02	1.05	1.20
$r_d$	0.021	0.235	0.505	0.114	0.093	0.11	0.108	0.155	0.306
$r_k$	0.045	0.107	0.065	0.011	0.012*	0.049	0.023	0.019	0.169
$r_{d, K}$	0.68	0.78	0.54	0.47	0.64	0.70	0.44	0.63	0.71

**Table 1.b**  $\eta = 36$ 

	$W = 3, \text{ pooled}$			$W = 3, \text{ sector}^{wa}$			$W = 1$		
	$\phi_{min}$	$\phi_{mean}$	$\phi_{max}$	$\phi_{min}$	$\phi_{mean}$	$\phi_{max}$	$\phi_{min}$	$\phi_{mean}$	$\phi_{max}$
<i>size</i>	256	192	139	85.33 <sup>a</sup>	64 <sup>a</sup>	46.33 <sup>a</sup>	249	196	131
$\rho$	0.28	0.21	0.14	0.73	0.62	0.42	0.71	0.50	0.32
$\chi$	0.88	0.99	1	1	1	1	1	1	1
<i>components</i>	1	1	3	1	1	1	1	1	1
$Q$	0.55	0.65	0.65	0.022	0.030	0.087	0.015	0.034	0.073
$C_N$	0.76	0.85	0.76	0.90	0.87	0.74	0.91	0.83	0.71
$C_N / C_N^R$	2.1	3.04	3.35	1.05	1.07	1.16	1.02	1.04	1.11
$r_d$	0.173	0.187	0.406	0.039*	0.027	0.169	0.043	0.128	0.233
$r_k$	0.082	0.039	0.093	-0.017	0.019	0.086	-0.012	0.045	0.122
$r_{d, K}$	0.84	0.75	0.82	0.68	0.74	0.84	0.67	0.75	0.81

**Table 1.** Properties of pooled, sector, and non-pooled networks, as produced by model simulations at  $\eta = 46$  (Table 1.a) and  $\eta = 36$  (Table 1.b).  $\phi_{min}$  (46) = 1,  $\phi_{max}$  (46) = 5,  $\phi_{min}$  (36) = 5,  $\phi_{max}$  (36) = 9.  $\phi_{mean} = (\phi_{min} + \phi_{max})/2$ . See appendix to section 3.2. $wa$  = cross-sector average weighted by sector relative size;  $a$  = simple cross-sector average $\rho$  = average degree / number of non-isolated nodes $\chi$  = ratio of within sector links to total links $Q$  = modularity $C_N$  = transitivity $C_N^R$  = transitivity in random network of identical size and degree distribution $r_d$  = coefficient of assortativity by degree $r_k$  = coefficient of assortativity by knowledge $r_{d, K}$  = Pearson correlation between degree  $d_i$  and endowment-size  $K_i$  of the *non-isolated* nodes.*components* = number of components of size larger than 2

\* negative assortativity in 1 sector

	1986-1989	1990-1993	1994-1997	1998-2001	2002-2005	2006-2009
Manufacturing	0.014	0.540	0.629	0.436	0.292	0.526
Services	0.748	0.532	0.677	0.732	0.569	0.502

**Table 2:** Pearson correlation coefficient between the size and the average degree of sector networks in manufacturing and services, four-years sub-periods, 1986-2009. Sectors identified by SIC three digits codes. Computation by the author based on Tables 1 and 4 in Tomasello et al. 2013.

Figure 1

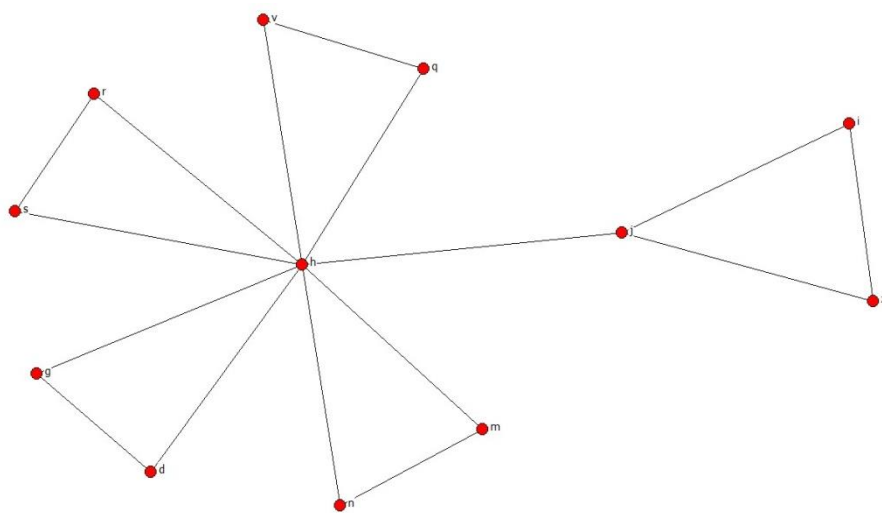


Figure 1. Network with 2 centre nodes  $h$  and  $j$  and 10 periphery nodes of degree 2. Each periphery node shares all its neighbors with each of its direct partners. Nodes  $h$  and  $j$  do not share any neighbor.