Research Article

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Knowledge diffusion and geographical proximity: a multi-relational networks approach

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Abstract: In the literature on innovation and organizational learning, there is a wide consensus about the relevance of learning activities. Specifically, they occur both individually (as producers will increase their knowledge simply "by doing") and collectively (as producers and other stakeholders involved will learn "by interacting"). Therefore, in these studies, the focus on informal learning has become increasingly evident with recognition that informal learning predominates in smaller and locally-operating firms, and large corporations alike. The aim of the study is twofold; firstly to understand the link between formal networks and informal learning and secondly to investigate if the information exchanged in the network between firms and institutions is altered by content. Through a case study in Foggia, southern Italy, we have investigated how knowledge flows among small organic food firms and related supporting institutions. The core finding of the study was that the existence of networks is necessary to promote informal knowledge flows, yet not sufficient by itself. In conclusion, several obstacles had to be removed before producers gained from the positive effects of geographical clustering and proximity.

Keywords: knowledge diffusion; informal learning; Social Network Analysis; multirelational networks

1 Introduction

In the literature on innovation and organisational learning, there is a wide consensus about the relevance of learning activities. Specifically, they occur both individually (as producers will increase their knowledge simply "by doing" – i.e. workers improve their productivity with practice The same also occurs at the group level as producers and other stakeholders share knowledge. Group learning "by interacting" occurs any time two actors exchange knowledge relevant to the production process on a voluntary and often reciprocal basis.

In these studies, the focus on informal learning has become increasingly evident based on recognition that informal learning predominates in smaller and locally operating firms, as well as being important for large corporations (Cho et al. 2018). Technical knowledge important to fomenting invention more likely passes up through similar channels (Sorenson and Sing 2009).

In small organisations the financial and opportunity costs of formal (i.e. institutional or planned) learning are typically perceived by the owner-managers as too great to bear. This is where informal learning comes to the fore, as ad-hoc or unplanned learning predominates to meet the immediate needs of the organisation. Theoretical and empirical studies suggest that such informal learning makes extensive use of peer and personal networks (Bala and Goyal 1995; Morone and Taylor 2004; Honkapohja and Mitra 2006; Mamaqi 2015; Bretschger et al. 2017).

It remains quite difficult to untangle formal and informal learning however as the former can itself result in the establishment of informal networks based on shared career paths (e.g. school, university, college, former employment), whereas the latter can influence the establishment of formal cooperation (e.g. hiring routines and links with institutions). Furthermore, there is an alternative path to enhancing the organisational knowledge-base, that of hiring knowledgeable employees. Although this clearly suggests that many sources for learning are to be found outside the organisation, the predominant view of the firm is that of the large organisation, meeting these challenges of innovation and learning from within.

The aim of this study is twofold: firstly to understand the link between formal networks and informal learning, and secondly, to investigate if the network structure changes with increasing content and information exchanged between firms and institutions.

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Specifically, thorough a case study in the south of Italy, we will investigate how knowledge flows among small organic food firms and related supporting institutions.

After focussing briefly on the role of multi-relational networks in knowledge diffusion (section 2), section 3 presents an analysis of the Social Network and Section 4 focuses on case studies and data analysis. Finally, some concluding remarks and policy implications are presented in section 5.

2 The role of multirelational networks in knowledge diffusion

The literature on Industrial Districts (ID) and on external economies emerging from the close proximity of actors in the process of economic activity had attracted the attention of many scholars (McDonald and Belussi 2003; Audretsch et al. 2007).

The core idea of these studies was the concept of industrial atmosphere, consisting of a business and social environment conducive to the acquisition of the benefits of proximity deriving from imitation, vicarious learning, quick adoption, and technical change and innovation introduced thanks to the generation of collective new knowledge.

Several authors, while studying ID, have focused their attention on the web of social interrelations developed by local actors. Studies regarding the performance of ID clearly reveal that the key factors of success are mainly the resources which are socially constructed, defined also as "advanced resources" (Porter 1990). Hence, the attention of researchers has been focused on two core aspects: firstly, on the co-operative relations between firms and the productive system including the socio-cultural-institutional environment in which they operate and secondly, on how such a system is able to produce positive outcomes for local operators (mainly in terms of the efficiency of knowledge diffusion).

Indeed, a considerable part of knowledge, which is involved in production processes is locally contextualized. In other words, it is not transferable from one place to another (as it is hard to interpret) and, as such, it can be defined as tacit. This kind of knowledge can be largely transferred in an informal manner by means of interpersonal relations between the operators involved in the production processes or by direct observations, thus becoming accessible only through the local contextualisation

Most of these learning processes are deeply informal, as tacit and uncodified knowledge can only be acquired and shared by means of intensive and direct interactions. Firms are perceived as distributed knowledge systems which are required to integrate efficiently specialized knowledge, both internally and externally, to perform innovations (Morone et al. 2011).

In this perspective it is particularly relevant to learn how tacit knowledge flows among local actors. Indeed, as pointed out by some authors (Bartlett et al. 1990; Tounkara 2013), a great deal of knowledge is, in this era of information and communication technology (ICT), still largely tacit in its nature and hence tightly bounded to informal (and face-to-face) interactions.

Some Authors (Morone et al. 2011; Ozmetel et al. 2011) point out as firms are capable of socially interacting, sharing information, and resources,they are also goal-directed in the sense that they can change their attributes as a reaction to environmental changes, directing their actions to the achievement of profit. In this view, modern social networks often consist of multiple relations among individuals. Therefore, a multi-relational network can be defined as a merger of multiple single relational networks. The multi-relational network as a survey unit is not new. These structures have been used in various disciplines ranging from cognitive science and artificial intelligence, to social and scholarly modeling (Wasserman and Faust 1994; Rodriguez 2007; Wang 2014).

Starting from the idea that processes of acquiring and transforming differentiated, dispersed, and localised knowledge are costly and require specific co-ordination activities (Morone et al. 2006), understanding the structure of such multi-relational network is essential. However, multi-relational networks are much more difficult to analyze than single relational networks. In a single relational network, grouping of nodes are identified by the density of the connections between them. In a multi-relational networks, such groupings can be identified by the different types of the connections, or rather combinations of relations.

3 Social Networks Analysis: some descriptive measures

Social Network Analysis has its historical roots in the disciplines of sociology, social psychology and anthropology, and it focuses on structural description of the networks. It represents a distinct research perspective within the social sciences as it is based on the assumption that relationships among interacting units are essential in understanding of individual and social dynamics. It therefore offers theories, models and empirical studies articulated in terms of relational analyses. This rapid increase of network research in several disciplines, and in innovation research in particular, has created the need for a review and a classification of studies done in this area.

The core unit of analysis is, of course, the social network, defined as "a specific set of linkages among a defined sets of persons with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behaviour of the persons involved" (Mitchell 1969). That is, "a social network consists of a finite set or sets of actors and the relation or relations between them" (Wasserman and Faust 1994).

Social Network Analysis provides an explicit formal way of measuring social structural properties and seeks to model the relationships among a set of actors to describe the structure of the group. The method of network analysis combines two different literatures, that on graph theory and that on matrix algebra[1]. This allows researchers to represent information about patterns of ties among social actors and enables representation of the structure of a system as a set of interconnected elements. Moreover, using these tools will allow us to evaluate and measure social relations and knowledge flows among individual actors, groups and organizations. In other words, social network analysis can be used as a valuable tool to measure the network's efficiency in diffusing knowledge.

The graph theory approaches a social network as a social system model consisting of a set of actors and the ties which exist between them. For the purposes of this paper, the social network is structured as a network graph consisting of nodes (vertices) and connections (edges). In other words we could define such a network as a "nonempty set of elements, called vertices, and a list of unordered pairs of these elements called edges" (Wilson and Watkins 1990). In our analysis, vertices correspond to firms or local institutions and edges are the existing connections. Formally, we can write G (I, Γ), where $I = \{1,\ldots, N\}$ is the set of nodes, and $\Gamma = \{\Gamma(i), i \in I\}$ gives the list of nodes to which each node is connected. The graphical display may prove to be inadequate with a growing number of actors and relations. Therefore, in order to get more specific information on the nature of relations and on the network properties (for example *network density* linked to more or less accentuated external economies) a matrix analysis would be a more useful tool.

When studying social networks, we must consider that fully saturated networks are rare, particularly where the population consists of more than a few actors. In this regard, it would be useful to look at how close a network is to realizing this potential. For example, the *density* of a sociomatrix is defined as the ratio of ties present to all possible connections. This index goes from *1*, if all possible ties are present, to *0*, if there are no lines present. It could be calculated as:

$$\Delta = \frac{L}{g(g-1)/2} = \frac{2L}{g(g-1)} \tag{1}$$

where:
Δ is the density of the graph
L the number of lines in the set
g the number of actors or nodes

Another property is *inclusiveness*: it refers to the number of points which are included within the various connected parts of the graph. That is the total number of nodes minus the number of isolated points. The most useful measure of inclusiveness, for comparing various graphs, is the number of connected points expressed as a proportion of the total number of points. An isolated vertex is a node with no connections, and thus contributing nothing to the density of the graph. Therefore, the more inclusive the graph, the denser it will be.

Furthermore, networks can have a few or many actors, and one or more kinds of relations existing between pairs of actors. To enhance our understanding of social networks we shall extend the analysis to another variable such as the nature of relations between actors. We can have, and this is especially true for firms, more than one kind of socio-economic relation, as they relate to different kinds of exchange. In order to deal with this further complication we shall consider *multi-relational networks*, which classify different types of social relations in the following two comprehensive categories:

- *material relations* (goods or money exchange, services, labour services, etc.)
- *communicative relations* (information and knowledge exchange).

As a final note, it is worth mentioning that we can categorize networks according to the nature of the sets of actors and the properties of the ties among them. The numbers of sets of entities on which structural variables are measured define the mode of a network. A *one-mode network* consists of a single set of actors, where the ties of each actor are enumerated. A *two-mode network* involves two sets of actors or one set of actors and one set of events. *An ego-centred* networks contain relational data on a focal actor (*ego*), a set of alter-actors who have ties to the ego, and the interconnections among the alter-actors

1 The conjoint use of both techniques should be avoided, as it is likely to generate graphs of different shapes from the same matrix.

(Wasserman and Faust 1994; Lopolito et al. 2011).

In the two-mode network, the first of the two interacting actors can be called the *sender* or *originator*, with the second, the *receiver* or *recipient* (or, simply, *actor* and *partner*). Furthermore, we can distinguish between *homogeneous* or *heterogeneous* pairs of actors, depending if they are from the same or from different sets respectively (Wasserman and Faust 1994).

4 The empirical investigation

As already mentioned, we concentrated our attention on an undeveloped area located in the south of Italy (in the province of Foggia) where we studied a group of formal institutions which support organic food production and a group of firms which are directly involved in the production of organic food. We studied a two-mode network, including the set of local firms operating in the organic sector and the set of the local institutions. In particular, we focused on how the firms relate to each other, how the institutions interact with each other and how the local organic firms are connected with the institutions.

In the area of Foggia there are 120 organic industrial firms out of which we chose a sample of 32 units selected with the *focus group*[2] technique.

However, undertaking a wide-ranging empirical analysis requires the collection of a large amount of "relational" data, which was obtained from the original sample augmented by 66 units following a *free recall* approach. With this technique, respondents were asked to name those firms with whom they had relations without referring to a fixed list (Cornwell and Hoagland 2014). Hence, we included in the sample those firms which were mentioned as a *link* by any firm originally included in the target sample.

The institutions supporting productive structures and activities of the organic sector in the area of Foggia consist of 33 units, out of which we chose a sample of 16 institutions[3]. Additional relational data were collected with the *focus group* technique in order to obtain the "roster of observable actors". This list included several actors external to the Foggia region but whom are still very relevant since from a dynamical perspective the absence of external relations could be the death of a system due to reduced innovative capability[4].

The organic sector was chosen in order to investigate the existence and extent of such informal mechanisms within a scenario of nominally formal relations.

The questionnaire, submitted with face-to-face interviews both to firms and institutions, was structured in two parts. The first part aimed at gathering general information on the characters of the firm or institution. The second part aimed to collect information on relations and, more precisely, on the existence or not of ties, their nature and, in the case of communicative relations, the kind of information exchanged (production system related, law system related, market system related)[5]. It is important to mention that a tie was established only if the existing connection was confirmed by both actors.

On the basis of this information, in order to understand the whole structure of the local organic sector, we studied the structural character of three different networks:

- the networking among local organic industrial firms;
- the local socio-institutional network supporting organic production (Sisto 2003);
- the interaction between the set of firms and the institutional system.

The research question was centred on the impact of informal interactions and the importance of geographical proximity in determining the knowledge flows among heterogeneous agents.

By means of questionnaires we collected information about the connections existing among firms and institutions involved in the organic food production.

4.1 Data analysis

Network descriptive measures as well as indices about general interactions and knowledge flows were analysed using the network analysis software toolkit UCINET 6.0 (Borgatti et al. 1999).

The analysis of the data has enabled us to study the network structure connecting firms with other firms, firms with institutions and institutions with other institutions.

Specifically, the analysis revealed the presence of a

2 In particular, in the study case, participants belonged to Local Public Institutions, Research centres, Entrepreneurial associations; Certification agencies (i.e. quality control agencies) from which interaction we obtained a draft of the "organic institutional network" and "organic firms network", whose structures were checked and corrected during the direct survey.

3 We are in the process of extending the analysis both to the universe of firms and institutions operating in the organic sector in the area of Foggia.

4 Note: a relation was classed as any social connection or set of interactions of the same kind between two individuals

5 Please refer to the appendix where the actual questionnaire used is supplied.

Table 1: Firms network indexes

Firms Network	Number of actors	Number of relations	Density	Inclusiveness
Network of interactions	66	56	2.6%	97%
Communicative network	66	37	1.7%	68%
Knowledge network	66	19	0.9%	38%

network[6] of 66 organic firms, linked by 56 undirected ties of different kinds (Figure 1).

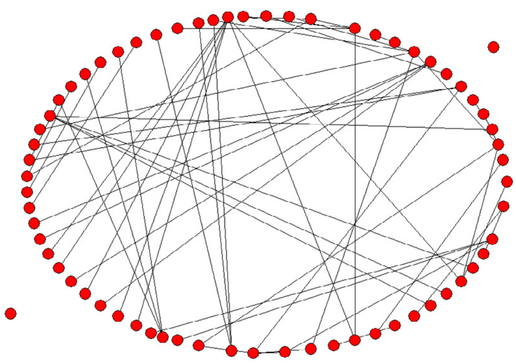

Figure 1: Network of interactions

It is clear that the network was not yet fully saturated since all possible ties were not present[7].

However, the network is cohesive enough, as it shows an inclusiveness of 97% (Table 1). In such a structure, most of the actors can reach each other one way or another.

As noted in Figure 1, only two firms are fully disconnected from the network. The original network was built regardless of the nature of the ties from which it was constructed. This means that it contains all kinds of ties connecting local firms, whether that be trade relations, information exchanges, or longer-lasting cooperative relations. This network (called a *network of interactions*, contains all identified relationships) simply describes the relational structure connecting the 66 firms.

As a follow-up step, we focused our attention on the nature of ties and on the structure of the resulting networks. According to multi-relational network theory, by distinguishing relations on the basis of their nature, it is possible to rebuild, with the same actors, new networks that are subsets of the whole network. For example, we can make a distinction between pure material relations from those that are also communicative.

As already mentioned, communicative relations are those through which firms exchange different kinds of information (production system related, law system related, market system related) useful to their activity. The selection of these relations enabled us to identify another network that we called *communicative network* (Figure 2) which is formed by a much lower number of undirected relations, 37 as opposed to 56. It results in a graph which is more disconnected, showing a higher number of isolated nodes (21 with respect to 2 of the former network) and obviously therefore much lower conclusiveness[8]. This suggests that only few of the firms interacting in the local organic sector are actually engaged in information and knowledge exchanges. This tendency is more accentuated if we make a further specification regarding the nature of the communicative relations. In fact, if we selected only those in which there was a real exchange of technical knowledge (information exchange that can affect directly the firm's productivity – i.e. what we called *production system related* knowledge), the network performance (which we can call a *knowledge network)* is heavily undermined (Figure 3). In this case, the picture has changed completely compared to the *interactions network* (see Figure 1) and we now have only 19 ties and 41 disconnected actors. Hence, the network is highly disconnected.

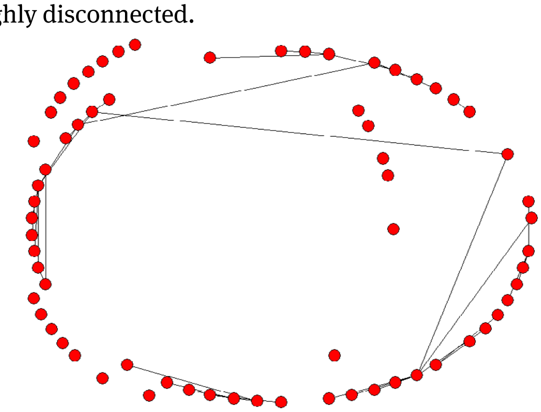

Figure 2: Communicative Network

6 The sociomatrix is a homogeneous and squared matrix of dimensions 66x66.

7 As the number of possible relations among 66 nodes is much higher than 56, the graph shows a fairly small density.

8 Which is, nonetheless, of 68%.

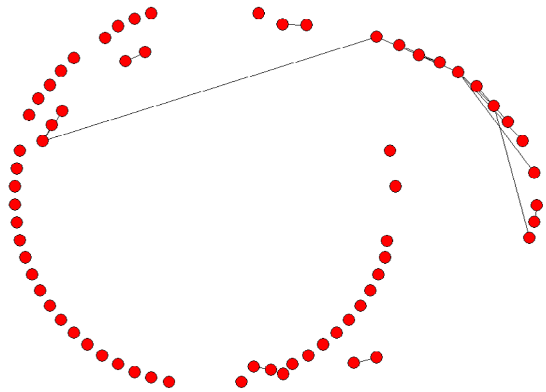

Figure 3: Knowledge Network

The analysis of the institutional network reveals the same tendency, although in a less heightened manner. As can be seen in table 2, the *network of interactions* among institutional actors, even if smaller than the firms' one[9], shows a higher number of undirected ties (59) which in turn shows generally higher cohesion (Figure 4a).

Only one actor is now isolated and the network density is of about 50%. However, this network also shows that these indexes undergo a substantial reduction if we consider the way in which knowledge flows:

in the *communicative network*, the number of ties decreases to 28 and the density is reduced to 23% (Figure 4b);

in the *knowledge network*, the number of ties decreases to 15 and the network density to 12.5% (Figure 4c).

The trend observed in the system of firms is confirmed in the surrounding social environment: the more we move from multiple relations to relations with a higher, more specifically informative content, the more the network becomes disconnected. It is only reasonable to expect that this will be confirmed from analysis of the network structure between firms and their surrounding institutional environment.

As to the question of how tacit knowledge flows within a region, we should know how it flows in the environment in which institutions and firms operate, because it seems improbable that the activity of the former would be unconnected from the latter. We therefore turned our attention to the network of firms/institutions to complete this question.

Therefore, we have investigated the network created between firms and the institutions sets. We obtained a dichotomous rectangular sociomatrix with dimensions 16 x 32, where the institutions are the senders while the firms the receivers of information and knowledge flows. The analysis showed the existence of a network in which 48 actors, linked by 106 directional heterogeneous ties of different nature, interact (Table 3).

For the three kinds of networks we can assert that there are directional relations from institutions to firms. The *network of interactions* (Figure 4)[10] is not fully saturated, but we observed a density (9.40%) higher than

9 The sociomatrix is a homogeneous and squared matrix of dimensions 16x16.

10 We used circles for firms and triangles for institutions.

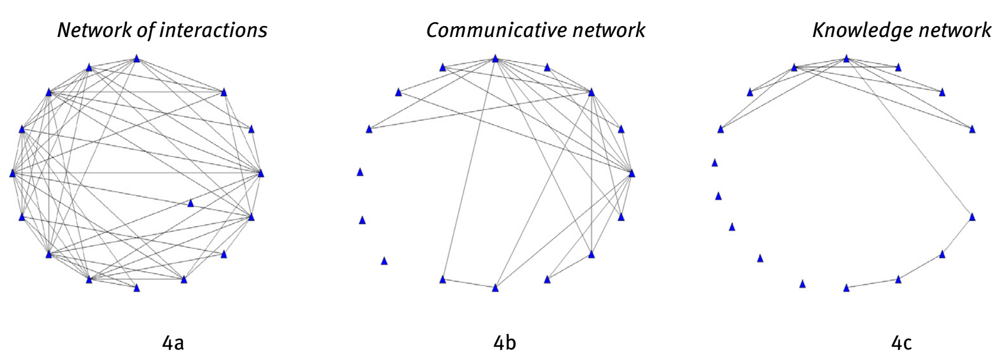

Figure 4: The socio-institutional environment

Table 2: Institutions network indexes

Institutions Network	Number of actors	Number of relations	Density	Inclusiveness
Network of interactions	16	59	50.0%	94%
Communicative network	16	28	23.0%	81%
Knowledge network	16	15	12.5%	69%

Table 3: Institutions - Firms network indexes

Firms-Institutions Network	Number of actors	Number of relations	Density	Inclusiveness
Network of interactions	48	106	9.40%	96%
Communicative network	48	101	8.95%	92%
Knowledge network	48	28	2.48%	52%

that for the firms' network, although it was much lower than that for the institutions. However, the network shows an inclusiveness of 96%; as seen in the graph, where only two actors are isolated (one firm and one institution).

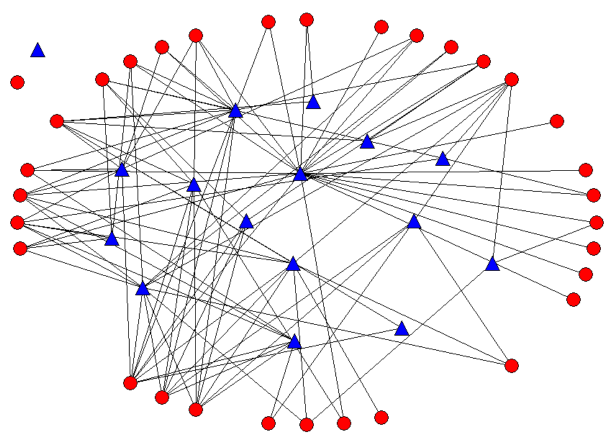

Figure 4: Network of interactions institutions-firms

In the *communicative network* (Figure 5) we have a smaller number of directional relations: 101 as opposed to 106 resulting in a graph which is slightly more disconnected than the one that shows four isolated actors (three firms and one institution) and a lower inclusiveness (92%).

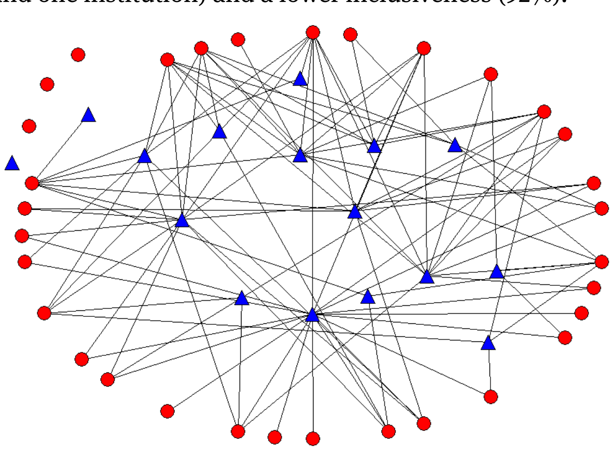

Figure 5: Communicative network institutions-firms

If we consider the third network, that of *knowledge*, the density drops to 2.48% and the inclusiveness to 52%. As expected, the graph is highly disconnected, as the number of isolated actors increases to twenty (12 firms and 8 institutions) (Figure 6).

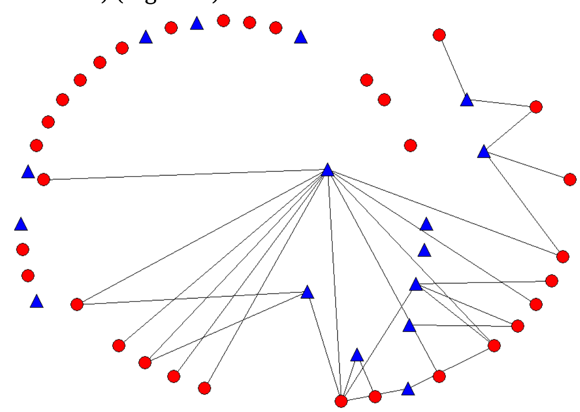

Figure 6: Knowledge network institutions-firms

Ethical approval: The conducted research is not related to either human or animal use.

4.2 Results

To comprehend which elements affect the structure of the networks examined and consequently knowledge flows, this section examines the three different kinds of networks and how their structure changes with the change of the nature of considered relations.

The network of firms shows the higher elements of weakness in terms of number of existing ties with respect to the potential number. Furthermore, this property is emphasized moving from interactions to knowledge networks. Such a of network would be indicative of the presence and diffusion of tacit knowledge among the firms located in a particular territory.

A first explanation could be that the interviewed firms and that had establish a network didn't belong to the same food supply-chain. In fact, district conditions are likely to establish within regions characterized by a typical production or belonging to the same supply-chain. A further explanation of the weak structure of the network could be the limited vertical or horizontal integration that affects firms located in the Foggia region.

At the same time, we noted a good interaction and basic communication among firms. For these, existing relations could be due to the sharing of a more exacting production process or with a particular market such as organic..

Moving to examine the network of institution, we see an improved general structure. Furthermore, with the changing of the nature of relations we find better properties. In fact, for the knowledge network which is usually the weaker one in relational terms, we find a density of 12,5%, that being the highest of the three knowledge networks analysed in this paper. This is explainable in two ways. A first element is related to the nature of the institutions questioned. In fact, being mostly in the organic sector, where it is known there is a greater tendency to exchange technical information.

The second issue is that, for different reasons, some are wont to establish cliques (Sisto 2003).

Finally, looking at the institutions-firms network, we see a lot of disconnected actors (either firms or institutions). This could be have been caused because of our own methodology in that we have considered only a sample and not all the existing firms and institutions. If we had considered them all, it is likely that some network properties could have been made worse, however it is also very likely that we wouldn't have had many isolated nodes.

5 Concluding remarks

The use and creation of knowledge is central to economic growth and development. This case-study has pointed out as in certain geographical contexts, notwithstanding the existence of a rather cohesive network, knowledge flows can remain a fairly marginalised element. In the light of this analysis, the existence of a rather cohesive network is not by itself a sufficient condition for positive outcomes associated with knowledge exchange in the surrounding environment, and the ID framework developed by industrial economists.

In other words, the analysis developed in this paper suggests that geographical proximity and the existence of cohesive networks is a necessary but not a sufficient condition to encourage flows of tacit knowledge in the surrounding environment. Local production systems need to remove various hurdles before being able to take advantage of the positive effects of agglomeration among firms and of their spatial proximity.

An early finding of this research has been that the organic sector under investigation does not appear meet the criteria of an ID, since the its measure of inclusiveness is too low with respect to knowledge flow.

Focusing our attention on how knowledge flows within the network, the study has argued that as the conditions found in an industrial district are rather complicated these could not be replicated in local areas which lack critical requirements for development (i.e. good infrastructure, access to modern technologies, endogenous capabilities to accumulate and innovate).

The core finding of the study is that the existence of networks is a necessary condition to promote informal knowledge flows, yet not in itself sufficient. When studying network behaviour, it is important to consider the nature of the network and the type of knowledge concerned. Moreover, some socio-political conditions have to be met if interested stakeholders want to play a proactive role in promoting such knowledge exchanges.

Hence, the fostering of knowledge diffusion requires a policy agenda able to stimulate knowledge creation and to facilitate sharing patterns among involved stakeholders.

Specifically, this would require the implementation of university-based initiatives designed to facilitate knowledge flows from the university (as well as other public institutions) to the firms or to direct public support to those firms most involved in knowledge generation activities.

In the end, several obstacles to the activation of knowledge exchange have to be removed before expecting to see the positive effects of geographical clustering and proximity. The identification of these obstacles will require further analysis of existing data as well as comparative studies in other geographical areas.

Conflict of interest: Authors declare no conflict of interest.

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Annex: Questionnaire used to collect the data

Date of interview: ______________________________

1. General information

Business name or Institution name ______________________________

Address ______________________________

Telephone ____________________ fax ____________________ e-mail ____________________

Manager ______________________________

2. Kind of activity

____

3. Existing Relations

Roster of Firms or Institutions	Existence of relation Yes/No	Relation's Nature				Kind of information exchanged (if there is a communicative relation)			indicate the source or the target
		trade related	firm property related	in-between 1 and 2	communicative	production system related	law system related	market system related	