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The Structure of Cluster Knowledge Networks: Uneven and Selective, not Pervasive and Collective

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Abstract:
This study focuses on the relationship between industrial clustering and innovation. It contributes to this literature by showing two empirical properties of the cluster learning process: first, that the structure of the knowledge network in a cluster is related with the heterogeneous distribution of firm knowledge bases and, second, that business interactions and inter-firm knowledge flows are not highly co-occurring phenomena. In particular, this paper highlights how the heterogeneity of firms' knowledge bases generates uneven distribution of knowledge and selective inter-firm learning.
This study has been based on empirical evidence collected at firm level in three wine clusters in Italy and Chile. Methods of social network analysis have been applied to process the data.

Key words: Industrial clusters, knowledge flows, business interactions, networks.

JEL Codes: O18, O30

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1 Introduction

Studies on industrial clustering date back to at least Alfred Marshall's contribution on economies of localization (1920). However, interest in spatially agglomerated industrial firms has risen mainly during the past thirty years, when the dominant model of the Fordist firm was questioned (Piore and Sabel, 1984) and geographical clusters of firms were seen as drivers of national growth and competitiveness (e.g. Porter, 1990; Krugman, 1991). Among the directions of research in this field, the relationship between industrial clustering,[1] localized learning and innovation has received rising consideration (e.g. Maskell, 2001a; Pinch et al. 2003). This paper contributes to this stream of studies, showing empirically that the process of knowledge diffusion and generation in clusters is uneven and 'selective', thus questioning the widely accepted view of cluster learning as being a pervasive and 'collective' process.

A widely accepted view is that knowledge is diffused and created in clusters in a pervasive and collective way, a view that is often shared by both economists and scholars of economic geography. On the one hand, economists stress the public nature of knowledge (Arrow, 1962) and argue that geography is conducive to innovation because of localized knowledge spillovers (e.g. Jaffe, 1993); on the other, recent work done by economic geographers argue that it is not geography *per se* that matters for innovation, but it is a common institutional endowment and firms' relational proximity, which facilitate the diffusion of knowledge and enhance collective learning in clusters (e.g. Maskell and Malmberg, 1999; Capello and Faggian, 2005). A common reason for this is the presumed co-occurrence between firms' business interactions[2] and inter-firm knowledge flows - a view consistent with the Marshallian 'industrial atmosphere' metaphor.

Recently, however, several contributions have expressed conceptual discontent with these views of clusters' innovation (see e.g. Breschi and Lissoni, 2001). Some have pointed out the need to understand the nature and characteristics of a cluster's innovative process by bringing in the analysis *firm-level* learning (Bell and Albu, 1999; Maskell, 2001b, Martin and Sunley, 2003), and more recently Giuliani and Bell (2005) have shown that the diffusion and generation of knowledge within a cluster is likely to be structured and differentiated according to the heterogeneity of firms' knowledge bases. Connected to this, others have questioned the co-occurrence of productive, business-related linkages and inter-firm flows of knowledge in the cluster (Bell and Albu, 1999) and have shown empirically that they may differ widely (Kishimoto, 2003).

This paper follows up this debate. Using methods of network analysis (Wasserman and Faust, 1994) it carries out an empirical study of three wine clusters - Colline Pisane (CP) and Bolgheri/Val di Cornia (BVC) in Italy and Colchagua Valley (CV) in Chile. It observes the emergence of two empirical properties: first, that the structure of the knowledge network in a cluster is related with the heterogeneous distribution of firm knowledge bases and, second, that inter-firm business interactions and knowledge flows are not highly co-occurring phenomena.

The paper is structured as follows: Section 2.1 reviews two widely influential views, which, in the literature, deal with the link between geographical clusters and innovation. Section 2.2 provides an alternative perspective of clusters' learning and innovation and elaborates original research hypotheses. Section 3 explains the methodology applied to this research and

[1] An industrial cluster is defined here as a geographical agglomeration of firms operating in the same industry, in accordance with Humphrey and Schmitz (1996) and Swann and Prevezer (1998).

[2] By business interactions I mean here any linkage that is formed among the firms in the cluster due to business-related matters - i.e. from vertical trade of inputs, to horizontal sharing of machineries, to participation in business fairs, etc.

the operationalization of concepts. Section 4 presents the empirical evidence and Section 5 discusses the results and briefly comments on possible policy implications.

2 Literature review and research hypotheses

2.1 The pervasive nature of knowledge diffusion in clusters

The process of knowledge diffusion and generation in clusters of firms has traditionally been based on differing re-interpretations of the Marshallian, externality-driven, world of industrial districts. Several empirical studies have elaborated on the Marshallian notion of knowledge spillovers.[3] I will mention here two widely influential views: (i) the economists' perspective on 'localized knowledge spillovers' and (ii) the economic geographers' view of cluster 'collective learning'.

The economists' view is that knowledge spillovers, which are by definition a public good (Arrow, 1962), tend to be highly localized (Jaffe, 1989; Jaffe et al., 1993), a property that conceptually links geography and innovation. Within this stream of studies, robust empirical evidence has shown that a relationship exists between spatial clustering, knowledge spillovers, and firms' innovative output (e.g. Audretsch and Feldman, 1996; Baptista, 2000). This empirical evidence has led scholars and policy makers to believe that geography matters for innovation and for competitiveness (e.g. OECD, 2001). As an example, in his work on industrial clusters and nations' competitive advantage, Porter (1990) connects the processes of learning and innovation in clusters to the 'Marshallian atmosphere' concept, stating that " the information flow, visibility, and mutual reinforcement within such a locale give meaning to Alfred Marshall's insightful observation that in some places an industry is 'in the air"' (p. 156). He notes in particular that "more important, however, is the influence of geographic concentration on improvement and innovation" (p. 157), since "proximity increases the speed of information flow within the national industry and the rate at which innovations diffuse." (p. 157).

Within the economics literature, however, the mechanisms by which geographic proximity is likely to generate innovation are not fully explored (Feldman, 1999; Anselin et al., 2000) and what tends to predominate is the conception of knowledge as a public good, which spreads pervasively within a spatially-bounded area - as in the case of a cluster. This limitation may well be due to the inherent ambiguity of the concept of localized knowledge spillovers (Krugman, 1991), which has received poor analytical treatment and it is to date considered by many as a 'black box' (Breschi and Lissoni, 2001).

Economic geographers have made attempts to open up this black box through a vast array of qualitative studies adopting multidisciplinary methods of analysis. They have now agreed that geographic proximity *per se* is not sufficient to generate learning and that economic space needs other forms of proximity to explain innovation (Boschma, 2005). Among these, a great emphasis is given to the role of social and relational proximity (e.g. Maskell and Malmberg, 1999; Amin and Cohendet, 2004). Industrial clusters, being a spatially localized set of economic activities, are in fact envisaged as 'embedded' economies (Granovetter, 1985) where social relationships, such as friendship and kinship, are entangled with business ones. More specifically, social proximity is believed to favour the formation of relational capital, defined

[3] Marshall described the industrial district as a place where "mysteries of trade become no mysteries; but are as it were in the air." (p. 225)

as a sort of productive 'thickening' based on market and cooperative inter-firm relationships (Scott, 1998). The relational capital, favouring the interaction of productive agents and the diffusion of tacit knowledge (Howells, 2002), is finally said to be the 'substratum' of collective learning (Capello and Faggian, 2005).

Economic geographers appear to have a more powerful interpretative framework to understand the *mechanisms* that link geography and innovation, if compared to economists' idea of localized knowledge spillovers.[4] The geographers' concept of collective learning differs from that of localized knowledge spillovers, since it more explicitly entails an interactive and cumulative effort by co-localized firms. As an example, Keeble and Wilkinson (1999) define collective learning in regions as " the creation and further development of a base of common and shared knowledge among individuals making up a productive system which allows them to co-ordinate their actions in the resolution of the technological and organizational problems they confront " (p. 296). In this literature, thus, collective learning processes are not merely an effect of firms' geographical co-localization but they are tied to a given "territory" (Camagni, 2002; Crevoisier, 2004) in which firms and people share common cultural values. Within this "territory", several "meso-level" mechanisms are envisaged as favouring inter-firm diffusion of knowledge and collective learning, among them: the turn-over of skilled labour, the intense client-supplier interactions, and the proliferation of spin-off firms. Finally, the combination of all these mechanisms result in unstructured and diffuse local interactions, consistent with Malmberg (2003) who mentions that " local interactions are characterized not just by being unstructured and unplanned, but also relatively broad and diffuse, sometimes unwanted and often seemingly of little immediate use." (p. 157). According to this view, the diffuse local interactions generate a learning environment where local knowledge, which is here conceived as an inherently private good, is shared through the short geographical *and* relational distance, thus becoming available as a public or a club good (Lawson and Lorenz, 1999). Hence, it should be noted that the essential characteristic of collective learning is that it still has a public dimension. As Capello (1999) put it:" the mechanisms for the spatial transfer of knowledge are *social* because new knowledge is transferred to other agents, whatever the will of the original inventor, thanks to common technological, organizational and institutional routines and behaviours which facilitate the sharing of information and know-how" (p. 356).
Put to the extreme, because of the centrality given to the public nature of knowledge either within a spatially or a relationally bounded area, both economists and economic geographers' views seem consistent with the Marshallian, externality-driven interpretation of clusters' learning and innovation. Recently, however, several contributions have expressed their discontent to this interpretation. These are elaborated and discussed in the following section.

2.2 Alternative perspectives and hypotheses of research

An alternative perspective to those discussed in the previous section, comes from other scholars who have recently expressed the need to include *firm-level* learning into the analysis of clusters' innovation (e.g. Bell and Albu, 1999; Maskell, 2001b) with the objective of understanding how firm-level and cluster-level learning processes interact. In this direction, Martin and Sunley (2003) argue that:

[4] On the interaction between geographical economics and economic geography see Martin and Sunley (1998).

> ‘The cluster literature’ lacks any serious analysis or theory of the internal organization of business enterprises (Best and Forrant, 1996). Instead it emphasizes the importance of factors external to firms and somehow residing in the local environment. In too many accounts local ’territorial learning’ is privileged, yet what this process actually is remains ambiguous and its interactions with firm-based learning are left completely unexamined (Hudson, 1999). (p. 17)

Using the expression ’territorial learning’, Martin and Sunley (2003) clearly refer here to the ’collective learning’ process occurring at the cluster level (cf. Martin and Sunley, 2003, p. 17) and stress the need to understand how such a process interacts with firm-level learning. I propose here a conceptual framework that allows this interaction to be explored. Starting from Nelson and Winter’s (1982) evolutionary theory of the firm, I argue that firms in the cluster are likely to be characterized by heterogeneous knowledge bases. By knowledge base I mean here the ”set of information inputs, knowledge and capabilities that inventors draw on when looking for innovative solutions.” (Dosi, 1988, p. 1126) Knowledge is seen as residing in firms’ skilled knowledge workers, who embody tacit capabilities, and at the same time, it is not merely the sum of each individual’s knowledge, since it resides in the organizational memory of the firm. As Nelson and Winter (1982) put it ”[t]he possession of technical ’knowledge’ is an attribute of the firm as a whole, as an organized entity, and it is not reducible to what any single individual knows, or even to any simple aggregation of the various competences and capabilities of all the various individuals, equipments, and installations of the firm.” (Nelson and Winter, 1982, p. 63) The knowledge base is moreover considered here as the result of a process of cumulative learning, which is inherently imperfect, complex and path-dependent (Dosi, 1997) and which delivers persistent heterogeneity between the firms in the economic system and, understandably in a cluster. Thus the question arises, *how does the heterogeneity in firm knowledge bases relate with the way knowledge is diffused among firms in the cluster, and hence with the structural characteristics of the cluster knowledge network?*

An argument here is that when firms seek advice on specific technical problems, for which they have no in-house solution, they *target* and *select* those firms, which are most likely to offer a better solution to the problem (von Hippel, 1987; Schrader, 1991). Reasonably enough, since networking is a time consuming and costly process, one should not expect firms to engage in inter-firm learning just randomly. Hence, it is firms with stronger knowledge bases that are likely to be perceived by other cluster firms as ’technological leaders’ in the local area, and that are sought out for technical advice more often than firms with weaker knowledge bases. Likewise, firms will ask for technical advice when they know that they will be able to absorb the received knowledge (Carter, 1989). This means that firms’ relative cognitive proximity (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998) is likely to affect the way in which knowledge is diffused within clusters. The implication of this argument is that one should therefore not expect knowledge diffusion in clusters to be simply collective, but rather, to be structured by the relative distance of firms’ knowledge bases (Giuliani and Bell, 2005). The first hypothesis is therefore elaborated as follows:

HP 1: THE STRUCTURE OF THE KNOWLEDGE NETWORK IS RELATED WITH THE HETEROGENEITY OF FIRM KNOWLEDGE BASES IN THE CLUSTER

This argument therefore provides a specific rationale for the structural characteristics of the knowledge network in clusters. Pushing the argument further, one may question the role played by the relational proximity of firms, discussed in Section 2.1, in the formation of knowledge linkages. *To what extent does relational proximity matter for the transfer of inter-firm knowledge?* One form of relational proximity is represented by e.g. productive linkages -

i.e. the trade of goods, services and inputs - formed at the horizontal and vertical level in the cluster. As mentioned in the introduction, insights into how productive linkages interact with the knowledge system have been recently provided by cluster scholars in the literature about developing countries. Bell and Albu (1999) have argued that knowledge systems are not identical to production systems and have stressed that, although they may interact with each other, their interaction is highly variable and poorly understood. Indeed, recent empirical studies have thrown light on the interplay between these two systems (Nadvi and Halder, 2002; Kishimoto, 2003) showing that they may diverge and involve different key actors, so that they should not be considered highly co-occurring phenomena. In this paper, I define business interactions not merely as the trade of goods or inputs but, broadly, as any interaction that occurs among firms for any matter related to their business. Thus, business interactions may include the trade of goods, as well as the transfer of information. They are therefore a reasonable approximation of firms' relational proximity. The question here is to what extent one should expect a substantial overlapping between the overall business interactions, as they have been defined here, and the inter-firm diffusion of knowledge.

In exploring this question, I adopt two positions. On the one hand, I am 'conservative' and I retain the assumption that business interactions occur in the 'Marshallian' way, thus being relatively pervasive in the cluster - consistent with Pyke at al. (1990) and Malmberg (2003), among others. On the other, I provide an interpretation of the knowledge flows in the cluster as being structured by the knowledge bases of firms - consistent with Hypothesis 1. Following this, two hypotheses have been developed, which are formulated below: the first one is that since business interactions and knowledge flows are driven by differing underlying rationales - the 'Marshallian' on the one hand, and the 'evolutionary' on the other - the network of business interactions will structurally differ from the network of knowledge. However, while it is reasonable to believe that they will differ, since the knowledge network will be a subset of the overall business interactions, the difference will be in a rather specific direction. I argue knowledge to be diffused more unevenly that one would expect if it was distributed primarily through the network of business interactions. In the latter case, in fact, the knowledge flows should be spread relatively evenly across the cluster - consistent with the localized knowledge spillovers and collective learning arguments discussed in Section 2.1. In contrast, in an 'evolutionary world', where firms have heterogeneous knowledge bases, the knowledge will be spread more unevenly. The following hypotheses are therefore elaborated as follows:

HP 2(a): The structure of the knowledge network differs significantly from that of the network of business interactions

HP 2(b): The diffusion of knowledge among firms with heterogeneous knowledge bases will be more uneven than one would expect if knowledge were to flow primarily through the network of business interactions.

3 Methodology

3.1 The data

This study is based on micro level network data, collected at the firm level in three wine clusters in Italy and Chile, namely: Colline Pisane (CP), Bolgheri/Val di Cornia (BVC) and Colchagua Valley (CV). The analysis has required careful data collection through interviews.

Interviews were carried out with the skilled workers (i.e. oenologists or agronomists). The survey was directed to producers of fine wines in each of the three clusters. Moreover, the analysis is focused only on inter-firm horizontal relationships, whereas vertical linkages are not explored here. The data were gathered using the universe of fine wine producers populating the three clusters,[5] which is of 32 in CP, 41 in BVC and 32 in CV, summing up to a total of 105 firms. Table 1 reports descriptive statistics on firm-level characteristics, such as their size, the ownership (i.e. whether they are foreign or domestic), and the year of localization in the cluster (i.e. whether the firm has started to operate in the cluster before the 1970s, in the 1980s, in the 1990s or after year 2000). Finally, the table includes information about the organization structure, distinguishing between four types: independent, vertically integrated firms, by which I mean firms that are not part of a larger corporation (i.e. they are independent) and that perform all the phases of the productive chain within the cluster. This type, which constitutes the vast majority of firms in the sample, differs from the cases in which local firms or plants are part of a group or a larger corporation and are either vertically integrated locally, thus performing all the phases of the productive chain within the cluster, or the are vertically disintegrated, in which case only a part of the production process is undertaken locally (e.g. grape-growing). Finally, a fourth type includes residual forms of organization structure (e.g. firms forming part of a cooperative).

Table 1: Description of the population of firms

Characteristics of firms by:	CP (N.32)	BVC (N.41)	CV (N.32)
Size (N. employees)			
Small (1-19)	91	90	28
Medium (20-99)	9	4	66
Large ($\geq$ 100)	-	6	6
Ownership			
Domestic	100	95	81
Foreign	-	5	19
Year of localization			
Up to the 1970s	53	25	24
1980s	9	16	22
1990s	31	38	23
2000s	6	19	15
Organization structure			
Independent, vertically integrated	88	66	93
Part of a group, vertically integrated	3	22	7
Part of a group, vertically disintegrated	-	13	-
Other (e.g. cooperatives)	9	-	-

Note: The numbers are percentages calculated considering the total number of firms in each cluster.

Apart from general background and contextual information, the questionnaire collected network data using a 'roster recall' method, which allowed two types of networks to be mapped.

[5] The lists of firms are drawn from official sources: the S.A.G. (Servicio Agricola y Ganadero) for Chile and the provinces of Pisa and Livorno for Italy. Further screening by key informants has also been performed.

The first one, which I call network of knowledge (KN) maps inter-firm flows of knowledge, which occur for technical advice purposes. It has been developed by asking the following two questions:

> *(KN1) If you are in a critical situation and you need technical advice, to which of the cluster firms mentioned in the roster do you turn?*
>
> *(KN2) Which of the following cluster firms do you think have benefited from technical support from this firm?*
> [Please indicate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none; 1= low; 2= medium; 3= high]

These questions specifically address problem solving and technical assistance because they involve some effort in producing improvements and change within the economic activity of a firm. This is meant to go beyond the mere transfer of information, whose access can be easily attained through other channels (e.g. trade fairs, the internet, specialized reviews etc.). So, for example, knowledge is transferred by providing a suggestion on how to treat a new pest or how to deal with high levels of wine acidity during fermentation. Accordingly, the knowledge transferred is normally the reply to a query on a complex problem that has emerged and that the firm seeks to solve.

The second network, defined as the network of business interactions (BI), maps the presence of linkages among firms of the same cluster, which may occur for any business matter - e.g. trade of inputs, participation in the same business association, exchange of information and the like. As such this network includes *also* the knowledge flows occurring among firms in the cluster. This network is used to measure the relational proximity of cluster firms. By providing the respondents with a roster of the population of fine wine producers in the cluster, the following question was addressed:

> *(BI)With which of the cluster firms mentioned in the roster do you interact for business matters?*
> [Please indicate the frequency of interaction according to the following scale: 0= none; 1= low; 2= medium; 3= high]

The interviews were also designed to obtain information that would permit the development of another quantitative indicator that is relevant for this present study: the 'knowledge base' of the firms. In the literature, this concept is often measured through information on training, human resources and R&D. Correspondingly, the structured interviews sought detailed information about the quality and experience of the technical human resources and about the quality of firm experimentation intensity - an appropriate proxy for knowledge creation efforts, since information about expenditure on formal R&D would have been both too narrowly defined and too difficult to obtain systematically.

3.2 Operationalization of concepts

The test of *Hypothesis 1* has required the operationalization of two concepts. The first one is the knowledge base of firms. This concept has been associated here with (i) the number of knowledge workers (i.e. oenologists and agronomists) employed full time by the firm, (ii) the months of experience of such knowledge workers in the wine industry, and (iii) the intensity

of the firms' experimentation activities. The latter is proxied by a scale ranging from a minimum of 0 to a maximum of 4, according to nature of experimentation. This information was then transformed into an operational indicator of the knowledge base (KB) using a Principal Component analysis.[6]
The second concept is the structure of the knowledge network. I have applied here a set of measures to provide a description of this network general structure. On the one hand, I have used indexes of actor-level degree centrality and, on the other, different techniques to identify cohesive subgroups.

Actor-level degree ($D_C(n_i)$) centrality refers to the extent to which an actor is central in a network on the basis of the ties that it has directly established with other j actors of the network:

$$D_C(n_i) = \sum x_{ij} \tag{1}$$

The actor-level degree centrality is calculated here considering indirected ties of the KN network, and it is a non-negative discrete variable that counts the number of linkages that a firm has established with other firms in the cluster.[7] In order to test Hypothesis 1, I estimate firm-level degree centrality of the KN network as a function of the firm knowledge base, using a negative binomial specification model with fixed effects (Cameron and Trivedi, 1986).[8] The model includes also firm and cluster dummies. Firm dummies are included to control for some key firm-level characteristics, namely the ownership (OWN), the year of localization in the cluster ($YEAR$) and the organization structure (ORG). A control variable for firm size ($SIZE$) measured by the number of employees, is also introduced in the model. Finally, cluster dummy variables ($CLUSTER$) control for the type of cluster.

Following the actor-level measures of network structure, I moved to the identification of cohesive subgroups of actors within the KN network. Cohesive subgroups are defined as "subsets of actors among whom there are relatively strong, direct, intense, frequent or positive ties." (Wassermann and Faust, 1994, p. 249) A set of methods and measures have been adopted in this paper to identify cohesive subgroups, among them I looked for *cliques*, $2-$*cliques*, *core* $-$ *periphery* models and $factions$. A *clique* is defined as a maximal subgraph of three or more nodes and it represents a subgroup of nodes which are all connected to each other. A $2-$*clique* is a maximal subgraph in which the largest geodesic distance between any two nodes is no greater than 2.[9] A *core*$-$*periphery* analysis allows the identification of a cohesive subgroup of core firms and a set of peripheral firms that are loosely connected to the core - as explained in Borgatti and Everett (1999). Finally, a $faction$ is a partition of a network done by grouping together actors on the basis of similarity to whom they are tied to (Hanneman, 2001).

The test of *Hypothesis 2(a)* has been based, first, on a simple measure of the network structure: network density (ND), defined as the proportion of possible linkages that are actually present in a graph. ND is calculated as the ratio of the number of linkages present, L, to its theoretical maximum, $g(g-1)/2$, with g being the number of nodes in the network

[6] A variant of this variable is also described in Giuliani and Bell (2005).

[7] I refer here specifically to the degree centrality calculated using dichotomous data.

[8] The baseline specification assumes that the dependent variable follows a Poisson distribution. The choice of the negative binomial specification is due to overdispersion in the dependent variable. For an application of this, see Nesta and Saviotti, 2005.

[9] On the concept of maximal subgraph, geodesic distance and on the formal definition of *cliques*, $2-$*cliques* see Wasserman and Faust (1994).

(Wasserman and Faust, 1994):

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

In order to test the structural differences between BI and KN networks, I applied Snijders and Borgatti's (1999) bootstrap-assisted paired sample t-test to BI and KN network densities. Beside this, a Quadratic Assignment Procedure (QAP) correlation (Borgatti et al. (2002) and Hanneman (2001)) was performed on BI and KN networks and I used the Jaccard coefficient to measure how much of the business interactions occur in the form of knowledge flows.[10]

Finally, the test of *Hypothesis 2(b)* has been based on two levels of measurament. First, I performed an analysis of the heterogeneity of the 'coreness' of each actor in both BI and KN network. By 'coreness' I refer here to the degree of closeness of each node to a core of densely connected nodes observable in the network, as described by Borgatti and Everett (1999). Using actor-level coreness data, I calculated two indexes of heterogeneity: Gini (G) and Hirschman/Herfindahl(HH). Second, I analyzed the distribution properties of actor-level degree centrality (D_C) of the two networks.

4 Empirical results

4.1 Uneven knowledge diffusion and the knowledge base of firms

This section analyzes the structural characteristics of the knowledge networks and explores whether they are related to the heterogeneity of firm knowledge bases in the clusters. Table 2 presents descriptive statistics of the three indicators used for the measurement of the firm knowledge base: (i) the number of knowledge workers, (ii) their months of experience in the industry and (iii) the experimentation intensity carried out at the firm level.

Table 2: Key indicators of firm knowledge bases and their heterogeneity

	CP				BVC				CV			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Knowledge workers	.34	.65	0	3	.56	.80	0	3	2.21	2.01	0	6
Months of experience	11	39	0	203	28	57	0	238	68	86	0	410
Experimentation intensity	.68	.95	0	3	1.09	1.35	0	4	1.59	1.43	0	4

To test Hypothesis 1, I start with the estimation of the degree centrality as a function of the firm knowledge base. The results of the estimation are reported in Table 3. The first column reports the estimations for the pooled sample. Columns (2), (3) and (4) illustrate the results for each of the three clusters: CP, BVC adn CV respectively. In the pooled sample, I find that firm knowledge base (KB) influences the expected degree centrality: the coefficient

[10]Note that, since the BI network *includes* the network of knowledge, the Jaccard coefficient may represent an 'overestimation' of the linkage co-occurrence between BI and KN networks.

is positive and significant at 5%. Strikingly enough, none of the firm-level control variables is significant. Significance is found for one of the cluster dummies ($CLUSTER - CP$), which means that, if compared with the baseline cluster CV, the expected degree centrality in Colline Pisane is going to decrease by 0.85%. These results lead to further exploration of the data by disaggregating them at the cluster level. As indicated in Column (2) the KB does not significantly influence the dependent variable degree centrality in Colline Pisane, whereas significant and positive results are found for both BVC and CV clusters.

Table 3: The relationship between degree centrality and firm knowledge base

Model	Pooled Sample	CP	BVC	CV
Intercept	1.33 (.63)**	-2.73 (1.64)*	.76 (.40)*	1.55 (.64)**
KB	.33 (12)**	-.10 (.46)	.35 (0.17)**	.57 (.18)***
$SIZE$	.017 (.12)	.49 (.35)	-.04 (.18)	-.08 (.15)
OWN	.44 (.43)	-	-	.44 (.43)
$ORG1$	-.66 (.58)	-	.38 (.47)	-.80 (.59)
$ORG3$	-.41 (.51)	1.53 (.95)	-	-45 (.45)
$ORG4$	-1.29 (.99)	-	-	-
$YEAR70$	.35 (.31)	1.02 (1.17)	.46 (.41)	.43 (.50)
$YEAR80$	.24 (.34)	.88 (1.34)	.52 (.45)	-
$YEAR90$	.20 (.31)	1.14 (1.19)	-.13 (.47)	.42 (46)
$YEAR00$	-	-	-	.27 (.51)
$CLUSTER - CP$	-.85 (.40)**			
$CLUSTER - BVC$	-.16 (.35)			
Log-likelihood	-206.09	-48.54	-79.18	-70.06
LR Chi Square	28.38***	6.36**	11.80**	12.41**
Pseudo R2	.06	.06	.06	.08

Note: $***, **, *$ indicate significant at 1, 5 and 10% respectively.
$ORG1$= Part of a group, vertically integrated; $ORG2$= Part of a group, vertically disintegrated; $ORG3$= Independent, vertically integrated; $ORG4$= Other
$YEAR70$, $YEAR80$, $YEAR80$, $YEAR790$ refer to the decade of firm localization in the cluster: 1970s, 1980s, 1990s and 2000 respectively.

Why is Colline Pisane so different from the other two clusters? The visualization of Fig.1 reveals that this cluster has a strikingly high number of disconnected firms, meaning that they are cognitively isolated from the rest of the firms in the cluster. Among them, the firm with the strongest knowledge base - indicated by the largest node size - is in fact entirely disconnected from the knowledge network. Qualitative evidence collected through the interviews suggests that the methods of production adopted by this firm are far more advanced than those commonly adopted by the other cluster firms, thus constituting a barrier to knowledge exchange. Instead, Fig.2 and Fig.3 show that in both the clusters of BVC and CV, firms with stronger knowledge bases (larger nodes) tend to show higher degrees of connectivity.

The analysis of cohesive subgroups provides further enlightening details on this. Its results are summarized in Table 4. It shows that Colline Pisane has a mostly disconnected-cliquish network structure, formed by five *weak cliques*[11] and one $2-clique$, as visible by Figure 1. The case of CP is one where most firms have equally weak knowledge bases, meaning that they do not employ skilled knowledge workers and that they carry out barely any in-house experimentation, as also shown in Table 2. Their very limited propensity to seek technical advice - consistent with the almost entirely disconnected network structure - may be due in fact to their weak internal capacity to search outside knowledge, thus to their very low absorptive capacity (Cohen and Levinthal, 1990).

In BVC the number of disconnected firms is lower than in CP (white nodes in Fig.2), and the knowledge network is faction-shaped, meaning that there are two sub-groups of firms that have similar patterns of cognitive inter-connection. These two factions differ in many respects. First, they differ in their average firm knowledge base: in one of the two factions, which I call here the 'advanced faction', represented by the darker nodes in Fig.2, firms have an average knowledge base of 0.61. In contrast, the corresponding average value for the 'laggard faction', indicated by the shadowed nodes of Fig.2, is -0.53. It is striking how these differences in firm knowledge bases can be associated with differing intra-faction densities. In this respect, the 'advanced faction' has higher density (0.17) than the laggard faction, where the density value is 0.07.

Finally, the knowledge network in CV has a clear core-periphery structure where, on the one hand, firms in the core tend to be highly interconnected among themselves and, on the other, peripheral firms tend to establish loose linkages with the core firms and virtually no interconnections with other peripheral firms. The density of knowledge linkages within the core is 0.32 for dichotomous and 0.57 for valued linkages. At the same time, the density of knowledge linkages among peripheral firms is 0.20 for dichotomous linkages and 0.26 for valued ones. In this case, firms in the core have, on average, stronger knowledge bases (0.58) than firms in the periphery (-0.45).

Table 4: The analysis of cohesive subgroups: a summary

	Structure	Cohesive Subgroups (Density)	Knowledge base (Average)
CP	Disconnected-cliquish	Clique: 0.10/0.12	Clique:-0.09
BVC	Faction-shaped	Adv.Faction:0.17/0.53 Lag.Faction:0.07/0.20	Adv.Faction:0.61 Lag.Faction:-0.53
CV	Core-periphery	Core:0.32/0.57 Periphery:0.02/0.26	Core:0.58 Periphery:-0.45

Note: Density values are reported both for dichotomous and valued network data.

[11] Scott (2000) defines weak cliques as those in which all ties are not reciprocated. The presence of weak cliques is particularly common in directed graphs as in this specific case of knowledge transfer.

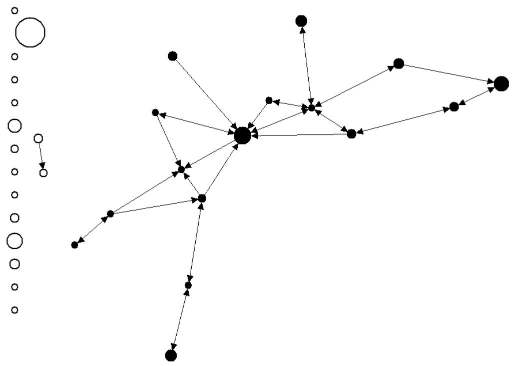

Figure 1: Knowledge network and the knowledge base of firms in CP

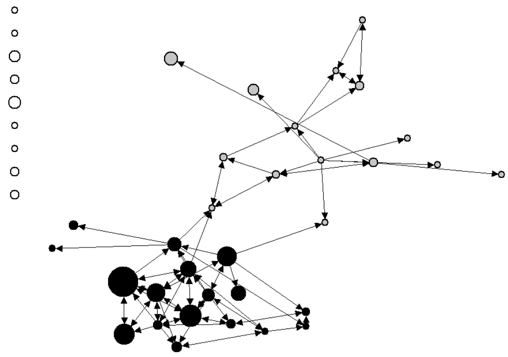

Figure 2: Knowledge network and the knowledge base of firms in BVC

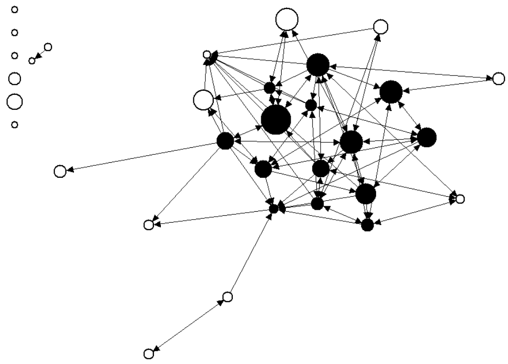

Figure 3: Knowledge network and the knowledge base of firms in CV

These results indicate that a relationship exists between firms' knowledge bases and the structural characteristics of inter-firm knowledge networks. Strongly significant coefficients were found in both BVC and CV between, indicating that firms with stronger knowledge bases tend to be more central in the knowledge network. This, as suggested in Section 2.2, may be due to the fact that firms with higher internal capabilities are perceived as 'technological leaders' in the local area and thus sought out for technical advice more often. In addition to that, firms with stronger knowledge bases are more capable to absorb knowledge spilling over from other equally or more advanced cluster firm and, therefore, they are more probable to form part of the knowledge network.

Where a significant estimation was not found, as in Colline Pisane, that was due to the highly disconnected knowledge network. There, the majority of firms are characterized by very weak knowledge bases an aspect that hinders inter-firm knowledge flows altogether. Besides, the relative cognitive distance between the majority of firms with weak knowledge bases and the only firm with more advanced techniques of production also contributes to the overall fragmentation of the knowledge network in CP.

The analysis of cohesive subgroups of also BVC and CV suggests that knowledge tends to flow in clusters in a highly polarized and uneven fashion. Knowledge is diffused primarily within the boundaries of one or more restricted subgroups of firms, as for example the 'advanced faction' in BVC and the 'core' in CV, with very limited knowledge spilling over to the rest of the cluster firms - i.e. the 'laggard faction' or the 'periphery' and no knowledge spilling over to disconnected firms.

These results validate Hypothesis 1.

4.2 Pervasive business interactions and selective inter-firm learning

Before testing Hypotheses 2(a) and 2(b), the visualization of BI and KN network data for the three clusters (Figures 4 to 9) suggests two striking features: first, that business interactions are visibly very similar across the three clusters and, second, that, consistent with the previous section, a much smaller number of firms is connected through the KN network. Density values are reported in Table 5, where the value for business interactions is significantly higher than the one characterizing knowledge networks:[12] in Colline Pisane the density of the BI network is 0.32, it is 0.20 in Bolgheri/Val di Cornia and 0.30 in Colchagua Valley. As expected, the density of KN networks is considerably lower in all cases ranging from 0.04 in Colline Pisane to 0.05 in Bolgheri/Val di Cornia and to 0.09 in Colchagua Valley. Table 5 also reports the results of the bootstrap t-test, which shows that BI and KN densities are statistically different, both in the case that the three clusters are taken separately and in the case in which they are pooled together in the same matrix (all t-values are higher than 2, the critical value). These differences tell us that only a minority of the overall business interactions are in fact knowledge flows. As shown in Table 5 the Jaccard coefficients resulting from the QAP correlation between BI and KN networks, have a strikingly low value in CP (10,4%), whereas the values for BVC and CV are slightly higher (25.8% and 28.1% respectively). However, these values may well be an an overestimation of the real co-occurrence between BI and KN linkages since part of the knowledge linkages may have formed without a different type of business interaction to have occurred at the same time (see Footnote 10).

In fact, qualitative evidence collected in the field suggests that this is often the case. Oe-

[12]Note that Table 5 also reports results for the pooled matrix data (Pooled). This matrix has been constructed by pooling together cluster level network data.

nologists or agronomists employed by cluster firms *select* the technical professionals working in the other cluster firms to whom they ask for advice. The selection is guided by two criteria: the first is the presence of a certain degree of homophily (McPherson et al., 2001) in terms of technical education (e.g. sharing of a common technical language) among skilled workers. Second, among those with similar technical education the search is oriented toward the ones that are more able to suggest a good solution to a problem. Hence, the knowledge workers, who are known for being highly experienced or for working in a technologically advanced firm, are more likely to be targeted for technical advice (Giuliani, 2005). Quite understandably, the selection criteria is driven more by cognitive motives than by any business interaction that the firms may have established on other grounds (e.g. trade of wine, lending machinery, participation in the same business association and the like). This clearly provides support to Hypothesis 2(a).

Table 5: Comparing BI and KN networks' density: results of the bootstrap t-test and Jaccard coefficient

	Network Density			
	BI network	KN network	t-test	Jaccard C.
CP	0.32	0.04	7.77*	0.104*
BVC	0.20	0.05	5.57*	0.258*
CV	0.30	0.09	4.48*	0.281*
Pooled	0.09	0.02	9.00*	0.217*

Note: ** Significant at 5%.

The test of Hypothesis 2(b) is carried out first by comparing the two inequality indexes of actor 'coreness' for both BI and KN networks. Results are shown in Table 6, which reports systematic higher values in the knowledge networks than in the network of business interactions. As an example, the Gini indexes for BI networks range between 0.324 in CP to 0.410 in BVC, whereas the value for the Gini coefficient in the case of the KN network ranges from a minimum of 0.609 in CV to a maximum of 0.871 in CP. These same features are found also applying the HH index to the data. This result depicts a more uneven distribution of linkages in the knowledge network and suggests that the structural differences between the two networks, previously observed by the analysis of the network density, are specifically related to the differing degrees of concentration of linkages across actors.

I explored this further by the analysis of the distribution of the actor degree centrality using the pooled dataset for both networks. First, I tested whether they have a Gaussian shape. I find that *only* the BI network's degree centrality follows a Normal distribution. In fact, the Kolmogorov-Smirnov test for Normality gives a p-value of 0.158 for the BI network thus not rejecting the null hypothesis of normality, whereas the distribution of the KN network's degree centrality is statistically different from the Normal (p-value=0.002). Following this result, I proceeded to a narrower inspection of the structural characteristics of the KN network. I find that, as illustrated in Fig. 10, the distribution of the KN network's degree centrality displays a highly skewed shape, approaching a power law distribution. The figure reports the linear fit and a non-parametric local regression obtained with a smoothing kernel

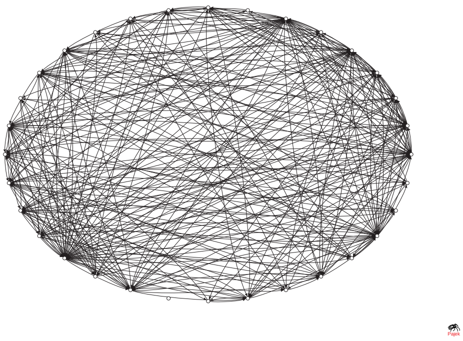

Figure 4: Business interactions in CP

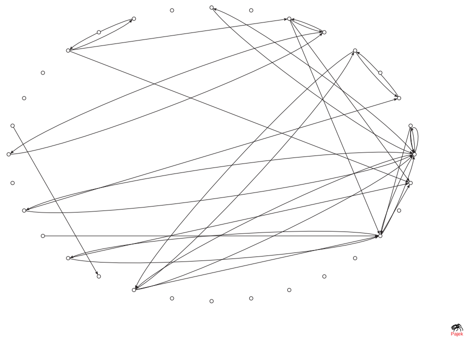

Figure 5: Knowledge flows in CP

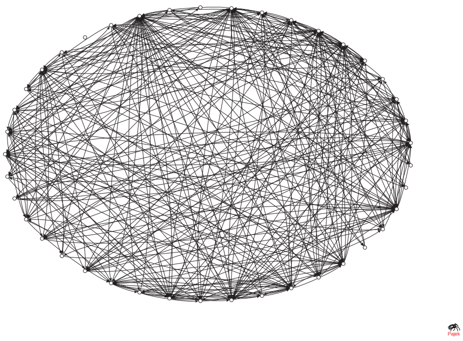

Figure 6: Business interactions in BVC

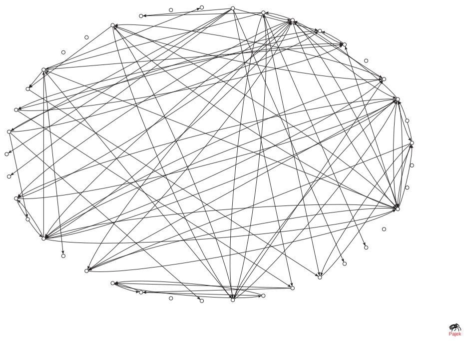

Figure 7: Knowledge flows in BVC

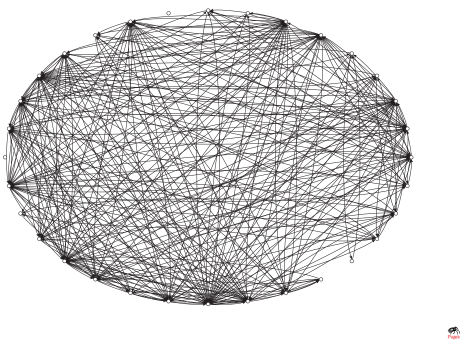

Figure 8: Business interactions in CV

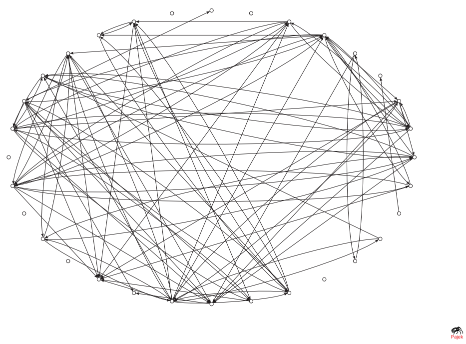

Figure 9: Knowledge flows in CV

Table 6: Measuring network heterogeneity: Gini and HH coefficients on actor coreness

	Gini Index		**H-H Index**	
	BI	KN	BI	KN
CP	0.324	0.871	0.010	0.311
BVC	0.410	0.806	0.014	0.091
CV	0.345	0.609	0.012	0.046
Pooled	0.786	0.923	0.031	0.104

method (dotted line).[13] I obtain a strongly significant slope $\beta = -0.94$ with a standard error of 0.12. As recently suggested by Barabasi and Réka (1999), a power law shape of degree centrality appears when a network is characterized by few nodes with extraordinarily high connectivity, whereas the majority of nodes have poor interconnection. These results support Hypothesis 2(b).

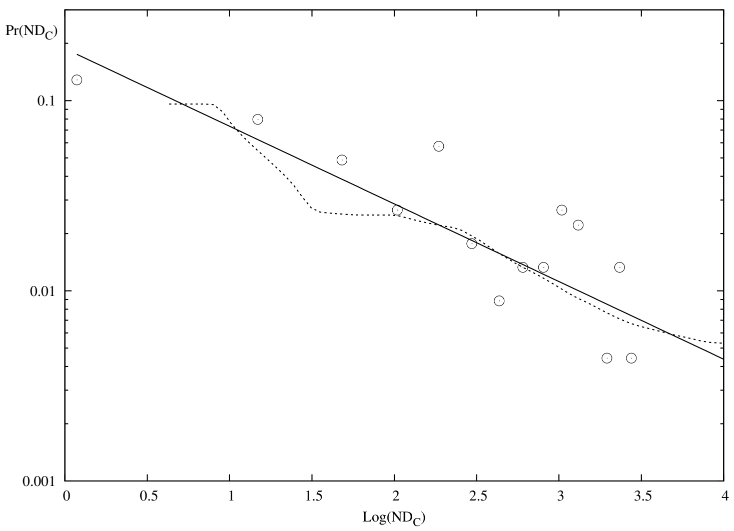

Figure 10: Empirical density of the knowledge network's ND_C together with a linear fit and a non parametric local estimate.

The evidence presented in this section suggests that the co-localization of firms in the cluster at least generates similar chances for firms to interact on business-related matters: the Normal distribution of the BI actor degree centrality may in fact be associated with a 'collective' view of firms' interaction in the cluster.[14] In contrast, the power law distribution

[13]See Pagan and Ullah (1999) for a description of the model. The kernel function used is the Epanenchnikov density with 0.371 as bandwidth. The estimate has been performed by a software package called gbutils developed by G. Bottazzi and available at www.sssup.it/~bottazzi/.

[14]Interestingly enough, following Erdos and Renyi's theory on complex networks, Barabasi (2003) associates the Normal distribution to a random network, where none of the nodes have a dominant position and where, therefore, the formation of linkage is pervasive.

can be seen as the result of a selective process over time. This distribution is in fact often associated with a 'preferential attachment' rule (Barabasi and Réka, 1999), which means that, as a knowledge network grows, there is a higher probability that a new node connects to the best-connected node in the network (known as the "rich-get-richer" phenomenon). This condition helps to explain the formation of large "hubs", characterized by extraordinarily high degree centrality values (Barabasi and Bonabeau, 2003).

5 Conclusion

This paper has attempted to open up the black box of 'localized knowledge spillovers' in industrial clusters. Using network data I was able to compare BI with KN networks, applying network theory to analyze their structural differences. The study has revealed that BI and KN differ in their network structure. Higher densities and relatively low values in the Gini and HH coefficients in the former network are consistent with the presence of *pervasive* business interactions among cluster firms. In addition, the Normal distribution of the degree centrality offers a 'collective' account of business interactions. This is compatible with the Marshallian 'industrial atmosphere' methaphor. However, the original contribution of this paper is that it has allowed the emergence of a second account, which is commonly overshadowed by the previous one. In spite of pervasive business interactions, inter-firm knowledge flows are strikingly limited to cohesive subgroups of firms. Consequently, they are unevenly distributed within the cluster. The power law shape of the knowledge network actor's degree centrality suggests in fact that only a *minority* of "'hub"' firms both contributes to and benefits from the presence of localized knowledge spillovers. Besides, the empirical analysis here suggests that this minority tends to be formed mainly by firms with similarly strong knowledge bases, whereas firms with weak knowledge bases are likely to be less connected.

This empirical evidence thus suggests that similar meso-characteristics -i.e. the geographic and relational proximity of firms - do not necessarily constitute the 'substratum' for collectively-shared knowledge flows. On the contrary, this study supports a *selective* view of cluster knowledge diffusion and learning processes.

On the basis of this, two considerations can be raised. First, bearing in mind that inter-firm knowledge flows may contribute to innovation, one should be extremely careful in associating the concept of industrial clusters to enhanced innovation capacity even when firms are geographically and relationally proximate. Instead, more rigorous studies should be carried out in the future that analyze the interplay between firms and the cluster knowledge network, where most of the innovation is likely to be generated. Second, as recently suggested by Markusen (2003), more rigorous analysis in regional studies will provide better indications for policy makers. Indeed, this study supports the view that innovation in clusters is more likely to be enhanced by strengthening firms' knowledge bases rather than by pooling firms together in the same geographical area (as is the case of 'technopoles', (OECD, 2000)) or by the promoting inter-firm and networking *per se* (UNCTAD, 2001; UNIDO, 2001).

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