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LAGGARD CLUSTERS AS SLOW LEARNERS, EMERGING CLUSTERS AS LOCUS OF KNOWLEDGE COHESION (AND EXCLUSION): A COMPARATIVE STUDY IN THE WINE INDUSTRY

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(DRAFT – Comments Welcome)

Abstract: This paper adopts sociometric analysis to explore the process of knowledge acquisition and diffusion in clusters of firms. By comparing the knowledge systems of two clusters selected for being at different stages of their development path, this study shows that the knowledge system of the laggard cluster is weak, highly disconnected and vulnerable, while in the case of the emerging, dynamic cluster, the knowledge system is characterized by a more connected yet uneven knowledge acquisition and distribution process. These differences are then interpreted considering the heterogeneity of firm knowledge bases across and within clusters and the impact of this latter variable on the degree of intra- and extra-cluster connectivity is explored.

Key words: Clusters, firm knowledge base, knowledge systems, social network analysis

JEL Classification: O14, O30, L20

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INTRODUCTION

This paper intends to contribute to the stream of literature that is concerned with the evolution of industrial clusters and focuses on the transition from laggard to emerging clusters. More specifically, this study adopts sociometric analysis to explore the cluster knowledge acquisition and diffusion processes. It does so by comparing the knowledge systems of two wine areas selected for being at different stages of their development path, i.e. a laggard one in Italy and an emerging one in Chile. In exploring the differences, this study tests whether inter-firm knowledge base heterogeneity, both across and within clusters, is correlated with the degree of firm intra- and extra-cluster knowledge connectivity. The main idea underlying this analysis is to try and understand whether it is possible to identify "micro-facts" or "micro-rules" that can affect the structural characteristics of a knowledge network and its liability to change over time.

The paper is structured as follows: Section 1 includes a critical review of both cluster and network studies and highlights the relevant research question and hypotheses of this present study. Section 2 concerns the methodology of research, its research design, the method of data collection and the operationalisation of relevant concepts. Section 3 presents the results of the comparative study by showing the differences of the two cluster knowledge systems, both at intra- and extra-cluster level. Section 4 tests the hypothesis of whether there is a correlation between firm knowledge bases and intra- and extra-cluster firm knowledge connectivity. Section 5 provides some conclusive insights and suggestions for further research.

1. CLUSTERS AND KNOWLEDGE NETWORKS: A THEORETICAL INTRODUCTION

1.1. Clusters and innovation: the perspective of development studies

The recent past has been characterised by an increased interest, both by academicians and policy makers, in industrial clusters of firms: in fact, while academic studies on clusters proliferated (see e.g. Special Issues of *Regional Studies* (33/4; 1999) and *World Development* (27/9; 1999)); cluster policies have been adopted in both advanced and developing countries and, in some cases, these have been considered drivers of national economic growth (UNCTAD, 1998; Porter, 1998; OECD, 1999; 2001).

Clusters, which are defined here as *geographical agglomerations of firms operating in the same or interconnected industries*[1] (Humphrey, Schmitz, 1996; Swann, Prevezer, 1998), gained momentum because, beyond static efficiency gains, clustering of economic activities proved to produce dynamic advantages, based upon processes of local accumulation of knowledge and collective learning (e.g. Marshall, 1920; Becattini, 1990; Camagni, 1991; Rullani, 1994; Maskell, Malmberg, 1999). This latter aspect has received increased consideration in the past decade. Quite consistently with the Marshallian original idea of "industrial atmosphere", this field of studies has evolved and has shown how clusters can be ideal locus of knowledge diffusion and generation.

A central argument that links clusters to innovation is the concept of *knowledge spillovers*, whose characteristics is that of being highly localised in space (Jaffe, 1989; Jaffe et al., 1993) and hence of diffusing easily within a geographically bounded area. In particular, what makes clusters highly conducive to knowledge spillovers is the fact that they allow *tacit* knowledge[2], which is sticky (von Hippel, 1994) and highly localised in principle (Nelson, Winter, 1982; Pavitt, 1987), to be transferred easily through eased contacts and face-to-face interactions. Drawing on this, several contributions have shown that a relation exists between spatial clustering, knowledge spillovers, learning and innovative output (among many others: Audretsch, Feldman, 1996; Baptista, 2000).

Hence, also on the basis of successful stories of some Italian industrial districts (e.g. Brusco, 1982; Becattini, 2003) and other productive local systems in different part of the industrialised world – e.g. Silicon Valley, Cambridge Region, etc. - (Scott, 1988; Saxenian, 1994; Storper, 1997), scholars have also promoted the idea that clustering could be a viable way to overcome competitive backwardness of informal, isolated SMEs in the developing world (e.g. Schmitz, 1992; Schmitz, 1995).

In laggard contexts, though, clusters appear far from the idealised model of the Italian industrial districts (Rabellotti, 1995) and from the innovative and dynamic areas of the Silicon Valley type; rather, different empirical studies (e.g. van Dijk, Rabellotti, 1997; Rabellotti, 1997; Nadvi, 1999; Schmitz, 1999; Yoguel, 2000¸ Cassiolato et al., 2003) have shown a heterogeneous set of experiences spanning from extremely poor performing clusters, with production mainly oriented to local and domestic markets, to more dynamic ones, which make an attempt to reduce the gap with

[1] The concept of cluster has been defined in many different ways by different cluster analysts (for a review see e.g. Martin, Sunley (2003)). In this paper I consider only sectoral specialisation and geographical concentration as a basic criteria for the existence of a cluster.

[2] The notion of *tacit* knowledge is normally referred to seminal contribution of M. Polany (1967), who noticed that people "know more than they can tell". He specifically referred to the fact that not all knowledge can be fully codified and therefore transmitted through distance. Instead, part of the knowledge is embedded in people, acquired through progressive experience and accumulated over time (e.g. learning by doing).

the technological frontier and to compete on the international markets (Altenburg, Meyer-Stamer, 1999).

One possible explanation for the existence (and persistence) of laggard clusters could be that their constituent *firms* are so far from the technological frontier that they are nor able to absorb extra-cluster new knowledge nor to generate a dynamic intra-cluster learning environment (Bell, Albu, 1999). Such a perspective reverses the most common view, which considers clusters' success as the result of the synergetic forces taking place at the "meso" level and promotes instead a more micro-centred view of cluster learning and innovation. In particular, this perspective dissents with the most acknowledged idea that "given that one of the major characteristics of developing countries is their weak technological base, technological spillovers within a cluster are crucial to its upgrading and ultimately to industrial development" (McCormick, 1999: 1533). And on the contrary, it considers the presence of weak knowledge bases as the *main* reason why localised knowledge spillovers should not be considered a good explanatory interpretation of cluster learning process in laggard contexts.

This paper intends to contribute to the above mentioned issue by: (i) showing the structural differences of the knowledge systems of two clusters characterised by different performance records – i.e. a laggard and an advanced one – and by (ii) shedding light on the link between micro-level knowledge endowments (i.e. inter-cluster differences in firm knowledge bases) and the structural differences of cluster knowledge systems. These two aspects are explored in the following two Sections.

1.2. Structural differences in the cluster knowledge system: why should we care about?

As anticipated, most cluster studies emphasise the power of localised knowledge spillovers for the learning and innovative capacity of clusters. But, while this might be a powerful interpretation of why clustered firms innovate more than isolated ones (Baptista, 2000), this shouldn't lead to think that clusters *per se* are good for innovation (OECD, 2001). By and large, cluster learning and innovative process is still unexplained; most studies lack of analytical rigour (Markusen, 2003) and are based on recurring fuzzy concepts like "knowledge in the air", "creative milieu", "diffuse innovative capacity", which subtract instead of adding clarity to the whole process.

In order to go beyond this and provide a more thorough understanding of the differences between e.g. learning-rich and learning-poor cluster knowledge systems, it seems that cluster studies could benefit from the adoption of sociometric methods and concepts. Mapping networks and analysing their structural characteristics could in fact allow to go beyond the fuzziness of "knowledge in the air" and similar metaphorical concepts.

And, indeed, sociometric analysis has been adopted in organisational and sociological studies to investigate the existence of a relation between network structure and organisational performance (e.g. Shan et al., 1994; Ahuja, 2000; Tsai, 2001; Reagans, McEvily, 2003). At inter-organisational level, contributions in this stream of studies have recently debated on the existence of an "ideal" knowledge network structure, which can be associated with high innovative performances. At this respect increasing attention has been devoted to the studies of dense networks á la Coleman (1988), to the importance of structural-holes (Burt, 1992) and to "small world" type of networks (Milgram, 1967; Watts, Strogatz, 1998).

Most probably, as recently noticed by Ahuja (2000), there isn't an "optimal" network structure for innovation and performance but, rather, different structures are likely to show different types of advantages and disadvantages. For example, dense networks tend to favour the formation of trustworthy linkages, which reduce the insurgence of opportunistic behaviours (Coleman, 1988; Rowley et al., 2000) and encourage cooperation and diffusion of more quality, fine-grained knowledge (Uzzi, 1997). Networks characterised by structural holes, instead, allow firms to expand the diversity of knowledge they can have access to (Ahuja, 2000) and reduce the probability of negative lock-ins (cf. Gargiulo, Benassi, 2000).
Similar to this, small world settings are considered a more desirable network structure than a randomly interconnected one, because fewer but more distant linkages enhance the probability of having access to diverse knowledge and allow efficiency gains in the processes of knowledge diffusion (Cowan, Jonard, 2004).

Although this paper is not meant to contribute to this latter debate, it is conceivable that the transposition of those results (and methods) at the cluster level, could benefit both cluster and network studies. Taken from a dynamic perspective, for example, an issue of potential interest would be to understand how a network structure changes with the progression of a cluster along its development path. Nevertheless, this is a too ambitious scope of analysis for this present paper that instead addresses the issue in a rather preliminary way. What it does, therefore, is simply to incorporate network analysis into a cross sectional study of two clusters selected for being at different stages of evolution: a baseline laggard and a dynamic emerging one. The following are among the primary questions that this analysis tries to answer: *how structurally different are the intra-cluster knowledge systems (i.e. the knowledge network formed by firms within the cluster)?* Particularly, *is knowledge simply randomly distributed in the air or does it follow structured patterns of knowledge diffusion and generation?* And, *is there a local intra-cluster knowledge* *system, which includes all cluster firms, or, does knowledge flow mostly within cohesive sub-groups of firms*? Said in another way, *are there firms that do not take part to the intra-cluster knowledge system?*

Moreover, since part of the learning process of a cluster has to do with their capacity to interconnect with extra-cluster knowledge (Camagni, 1991; Bell, Albu, 1999), it seems relevant to explore the following questions: *are firms all equally connected to the extra-cluster sources of knowledge?* And, *how much of the externally acquired knowledge, percolates into the intra-cluster knowledge system?*

1.3. Exploring the micro-meso link for cluster success: why it is important

Both cluster and network studies tend to consider the *meso*-level (i.e. a cluster or a network of firms) as the unit of analysis. And hence most of research has been undertaken to analyze the effects of meso-level characteristics (e.g. degree of inter-firm co-operation, presence of localized knowledge spillovers, structural features of the networks, etc.) on the innovativeness and performance of the cluster or network.

Less research has instead been directed to the understanding of how the meso-level characteristics come into being or evolve as a results of micro-level, non-structural characteristics.

In the domain of cluster studies, for example, only relatively few contributions have shed light on the relation between intra-firm characteristics and the innovative outputs of clusters or regionally bounded areas (see, Harrison et al., 1996; Albaladejo, Romijn, 2003; Giuliani, Bell, 2004; see also Beaudry, Breschi, 2003). As suggested by Caniels and Romijn (2003), "the regional agglomeration studies emphasize the favorable impact of geographical proximity on regional economic performance; but the firms that constitute those agglomerations largely remain black boxes. In contrast studies dealing with technological learning explain economic performance at firm level without systematically taking accounts of the effects of geographical proximity" (Caniels, Romijn, 2003: 1253).

Similarly, in network studies, recent contributions have stressed that: "the bulk of network research has been concerned with the consequences of networks" (Borgatti, Foster, 2003: 1000) and that "…limited attention has been paid thus so far to how important nonstructural features – such as the characteristics of the organizations that represent nodes in a network, geographic location, or the institutional underpinnings of the larger structure – alter the character of information flows." (Owen-Smith, Powell, 2004: 5).

In addition, while considerable research effort has been directed to the analysis of clusters and networks at a point in time, less consideration has been given to their dynamism, that is, to their processes of evolution and change over time (e.g. Schmitz, Nadvi, 1999; Borgatti, Foster, 2003).

Hence, it is believed here that, while structural characteristics of networks are important for the impact that they might have on the final output of the economic phenomenon observed, it is non-structural variables that ultimately might influence the way in which such structural characteristics come into being and change over time (or don't).
Among all possible non-structural variables this paper focuses on the knowledge base of firms. Defined as the "set of information inputs, knowledge and capabilities that inventors draw on when looking for innovative solutions" (Dosi, 1988: 1126), the knowledge base of firms is the result of processes of path dependent accumulation of knowledge over time. Heterogeneity in firm knowledge bases gives rise to intra-firm imbalanced cognitive positions and to different degrees of external openness, which shape the cluster knowledge system accordingly (see on this: Giuliani, Bell, 2004). Hence, as firms strengthen their knowledge bases, they are better able to absorb extra-cluster knowledge (Cohen, Levinthal, 1990), and to participate actively in the intra-cluster knowledge system, by promoting knowledge diffusion and exchange at intra-cluster level (i.e. behaving as technological gatekeepers– Allen (1977), Tushman, Katz (1980), Gambardella (1993)). Conversely, firms with lower knowledge bases have a residual role in both extra-cluster knowledge absorption and intra-cluster knowledge diffusion and generation, thus behaving as isolated firms (Giuliani, Bell, 2004).

Consistently with this argument, I expect that clusters characterized by weaker firm knowledge bases have also weaker knowledge systems, which means that their knowledge connectivity at both intra- and extra-cluster level is low. In order to explore this relation, I narrowed down the focus at firm level and considered the patterns of intra- and extra-cluster connectivity of both cluster firms to test the following hypotheses:

Hypothesis (1 a): Firm knowledge bases and degrees of firm interconnection at intra- cluster level are positively correlated.

Hypothesis (1 b): Firm knowledge bases and degrees of firm interconnection at extra- cluster level are positively correlated.

By testing these hypotheses, I expect to understand whether the cognitive endowments of firms are related to their capacity to link with other firms at intra-cluster level and to establish extra-cluster knowledge linkages.

2. METHODOLOGY

2.1. Research design: the selection of clusters

The empirical analysis presented here consists of a comparative study between two different *wine* clusters – Colline Pisane and Colchagua Valley – localised into two different countries: Italy and Chile. It is a feature of the research design that these two clusters were selected for being "at different stages of their evolutionary path". According to their performance records, Colline Pisane qualifies for being the laggard one and Colchagua Valley for being an emerging, dynamic cluster.

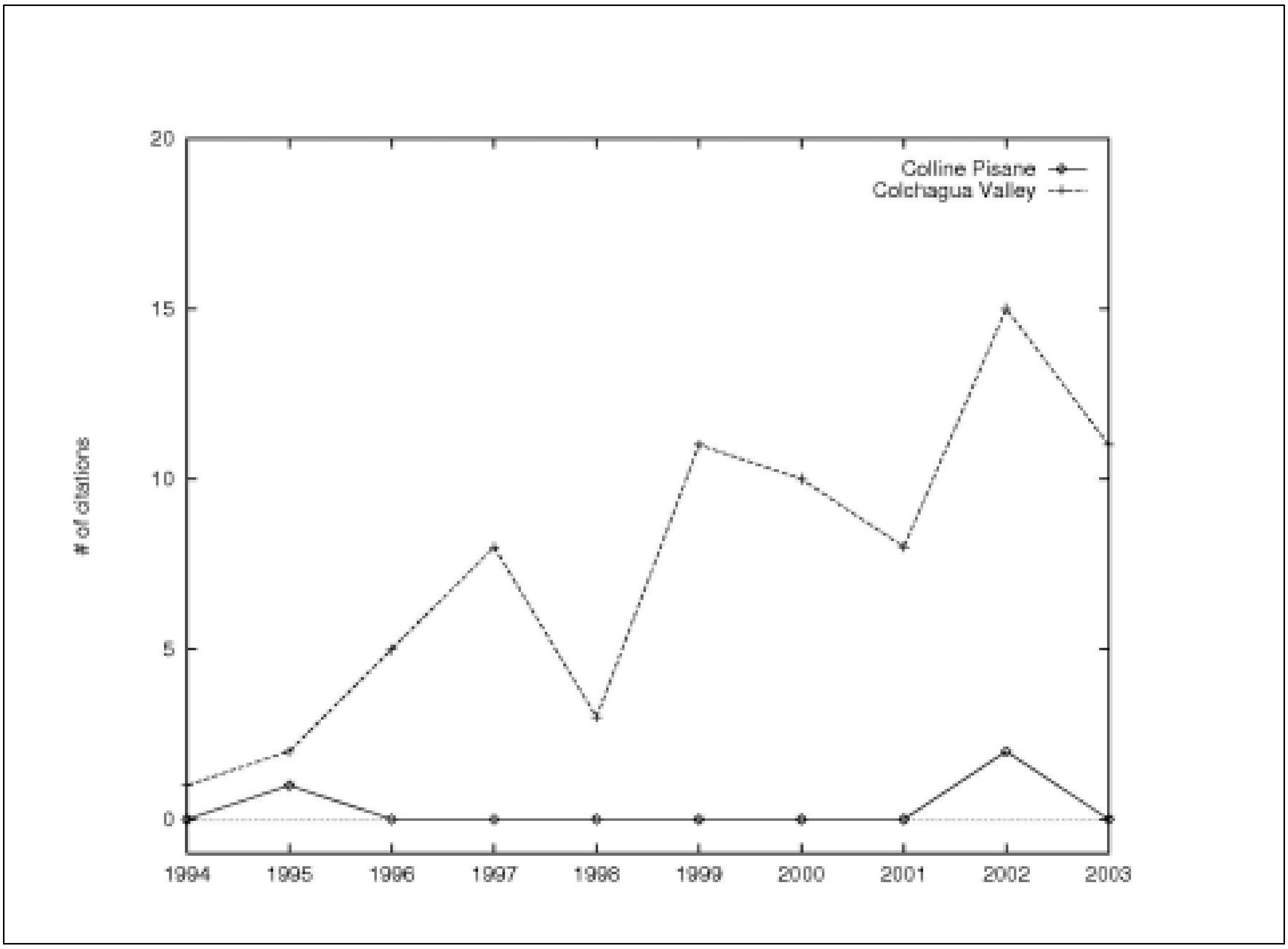
Indeed, the selection was based on secondary data sources, drawing from five international journals specialised in the wine industry[3]. These journals provided information on: (i) the reputation of each wine area; (ii) the qualitative standards of the wines produced in each area.

As regards (i), data gathered in the Wine Spectator 1994-2003 Archives allowed to count the number of times each wine cluster was *cited* in that journal's articles. I considered the citation as a rough proxy of the international reputation of each wine area.[4] Results are shown in Figure 1.

[3] The journals selected are the following: *Wine Spectator, Robert Parker Independent Consumer's Guide to Fine Wines, Wine Enthusiast, Decanter and Tastings*.

[4] Since wine is considered an hedonic good, the good reputation of the area where it is produced influences positively the final price and allows higher value added and higher margins of profit for firms in the area.

Figure 1: Cluster reputation's indicator (1994-2003)



Source: Own elaboration based on *Wine Spectator* Archives (1994-2003).

Clearly, Figure 1 shows a gap between the citation patterns of the two clusters, which tend to have increased over the period considered. More specifically, while Colline Pisane is hardly cited over the period, Colchagua Valley is cited more over the years.

As concerns (ii), other four international journals (*Robert Parker Independent Consumer's Guide to Fine Wines, Wine Enthusiast, Decanter and Tastings*) were taken into consideration. Drawing on these sources, I counted the number of wines that went through a quality assessment process by expert referees and where mentioned in each of the selected journal in 2003.[5] I considered this count a rough proxy of the quality of products for the year considered. Results are consistent with the analysis of Wine Spectator's archives – see Table 1 for a summary.

[5] I counted the number of wines, which have undergone referral processes, not the ratings. Even so, the fact of being rated by an international wine review is in itself a sign of quality recognition.

Table 1: Cluster performance indicators: a summary

Cluster	Cluster reputation (# citations of each cluster, years 1994-2003)	Firm wine quality indicator (# citations of single wines in specialised journals, year 2003)			
		Robert Parker	*Wine Enthusiast*	*Decanter*	*Tastings*
Colline Pisane	3	16	15	0	1
Colchagua Valley	91	53	134	39	15

Source: Own elaboration based on *Wine Spectator* (1994-2003), *, Robert Parker Independent Consumer's Guide to Fine Wines Wine Enthusiast* (2003), *Decanter* (2003) and *Tastings* (2003).

These results have been complemented by interviews to key informants of the industry carried out during both pilot fieldwork, in Chile and Italy, and by other collateral readings. All sources supported the view of Colline Pisane being relatively laggard with respect to Colchagua Valley and of the latter being an emerging, dynamic cluster.

2.2. Collection of data and sample features

2.2.1. Method for collection of data

The empirical study proceeded through the collection of primary data at firm level. Fieldwork projects were undertaken by the author in both Chile and Italy in-between September and December 2003. The collection of data was based on interviews, conducted directly with the technical personnel of the firms – i.e. the oenologist, agronomist or the entrepreneur (in the case of lack of technical professionals in the firm). A structured questionnaire was adopted for the purpose and relational data on firm knowledge linkages were collected through a roster recall method.

Apart from general background and contextual information, the interviews sought information that would permit the development of quantitative indicators of (a) the intra-cluster knowledge system; (b) the degree of firm connectivity with extra-cluster sources of knowledge; and (c) firm knowledge base.

(a) the intra-cluster knowledge system

By intra-cluster knowledge system, I consider the flows of technical knowledge transferred within the cluster boundaries by firms operating as wine producers. Therefore, the intra-cluster knowledge system includes horizontal knowledge flows, based on technical advice seeking processes. In order to collect such data, in the questionnaire-based interview, each firm was presented with a complete list (roster) of the other firms in the cluster, and they were asked the following questions:

Q1: Technical support received [inbound]
If you are in a critical situation and need technical advice, to which of the local firms mentioned in the roster do you turn? [Please indicate the importance you attach to the information obtained in each case by marking the identified firms on the following scale: 0= none; 1= low; 2= medium; 3= high].

Q2: Transfer of technical knowledge (problem solving and technical advice) [outbound]
Which of the following firms do you think have benefited from technical support provided from this firm? [Please indicate the importance you attach to the information provided to each of the firms according to the following scale: 0= none; 1= low; 2= medium; 3= high].

Respondents were asked to provide *ratings* for each question. The ratings ranged from a minimum value of 0 to a maximum of 3. The respondent was asked to attribute a value of 3 to those relations that contributed significantly to the process of technical change of the firm – in terms of both quality and persistence of linkages – whereas lower values were attributed to minor contributions.

(b) The acquisition of knowledge from extra-cluster sources

The interview also asked about the firms' acquisition of knowledge from sources outside the cluster, both at national and international level. Specifically, respondents were asked to name on a roster of possible extra-cluster sources of knowledge (universities, suppliers, consultants, business associations, etc.) those which had contributed to the technical enhancement of firms. They were also asked to indicate whether the firm had co-operated with any of those sources for joint research and experimentation. More specifically two different questions were formulated:

Q3**: **Technical support received [inbound]
Question Q3: Could you mark, among the actors included in the roster, those that have transferred relevant technical knowledge to this firm? [Please indicate the importance you attach to the information obtained in each case by marking the identified firms on the following scale: 0= none; 1= low; 2= medium; 3= high].

Q4: Joint experimentation
Question Q4: Could you mark, among the actors included in the roster, those with whom this firm has collaborated in research projects in the last two years? [Please indicate the importance you attach to the information obtained in each case by marking the identified firms on the following scale: 0= none; 1= low; 2= medium; 3= high].

(c) firm knowledge base

The structured interviews sought detailed information about (i) the number of technically qualified personnel in the firm and their level of education and training, (ii) the experience of professional staff – in terms of time in the industry and the number of other firms in which they had been employed, and (iii) the intensity and nature of the firms' experimentation activities - 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. This information was transformed into an operational indicator of firm knowledge base as described in Section 3.2 and in the Appendix.

2.2.2. Sample features

The samples include 32 firms in each cluster, which account for the total population of fine wine producers in both cases. A total of 64 wine producers was therefore interviewed. It is pertinent to note that the survey included only firms operating as wine producers. Thus, due to the limited degree of vertical disintegration in these industry clusters and to their very limited relevance in the processes of cluster learning and innovation, grape-growers were not considered in this present analysis.

The wine producers included in the analysis characterised for being either: (i) vertically integrated, locally-based firms producing branded wines, usually for quality markets; or (ii) local subsidiaries of big national wineries, also producing branded wines, for quality markets[6]. Clearly, firms differed in terms of their size and scale of production, with firms in Colline Pisane being smaller-sized than those of Colchagua Valley. Finally, only a minority of firms, were foreign-owned (see Table 2).

Table 2: Characteristics of sample firms

	Colline Pisane	**Colchagua Valley**
Type of firm:		
Vertically-integrated, locally based	31	25
Local subsidiary of national firm	1	7
Size:		
Micro-Small	31	9
Medium	1	21
Large	0	2
Ownership:		
Domestic	32	26
Foreign	0	6

Source: Author's own

[6] Both samples include a small percentage of local producers of bulk wine, usually at low quality. These were counted among the vertically integrated locally based firms.

2.3. Operationalisation of concepts into analytical measures

2.3.1. The intra-cluster knowledge system

The local knowledge system has been analysed through graph theoretical methods (Wasserman, Faust, 1994), which allow to trace the *structure* of the local system of knowledge and to identify patterns of knowledge diffusion.

Merging questions Q1- and Q2-related datasets, I formed a unique matrix, which has been used to map the intra-cluster knowledge system[7]. The analysis is organised according to two highly interrelated dimensions: the first one concerns the intra-cluster knowledge system and therefore its characteristics as a *set of interconnected nodes;* and the second one regards the *positions of nodes* in the network. To analyze the former, I considered the following measures (see Appendix for major details):

(i) *network density*, which is a measure of the degree of interconnection of firms with the intra-cluster knowledge system;

(ii) *network strength of ties*, which measures both the persistence and quality of relations. As said, strong linkages – valued 3 – imply persistent and fine-grained knowledge transfer or absorption, while weak linkages – valued 1 – imply occasional and less sophisticated knowledge transfer.

(iii) *structural characteristics* of the network, with particular reference to the formation of *cohesive subgroups*, which are sub-groups of firms that have established more relations with members internal to the subgroup than with non-members (Alba, 1973). Among cohesive subgroups the analysis considered:
   a. *clique* and *2-cliques;* the former are cohesive subgroups in which all nodes are directly connected the one with the other; the latter are a relaxed version of the former, which allows 1 intermediary step in the connection of nodes.
   b. *core-peripheral* structures are structural characteristics of the network by which a cohesive core of firms is loosely connected to a periphery of firms (see Borgatti, Everett, 1999).

To analyze the position of nodes in the network, I considered:

(iv) *firms' degree of centrality* (Freeman, 1979), which was measured considering:
   a. *in-degree centrality*, which refers to the number of linkages that are incident to a node and therefore represents the propensity of a firm to acquire knowledge from other intra-cluster firms;

[7] In substance, then, what I address as intra-cluster knowledge system is an advice network.

b. *out-degree centrality*, measured by the number of linkages that depart from one node and represents the capacity of a firm to transfer knowledge to other cluster firms;

c. *betweenness centrality* is a measure based on the firm being on the geodesic distance (i.e. the shortest path) connecting other actors in the network, therefore it measures the capacity of a firm to connect distant firms in the cluster.

(v) *firms' intra-cluster cognitive positions*, which refer to firms behaving as sources, absorbers, mutual exchangers of knowledge or as isolated firms, so that:

a. *sources* are those firms that transfer more knowledge than they receive at intra-cluster level, in which: in-degree < out-degree centrality;

b. *mutual exchangers* are those firms that absorb as much knowledge as they transfer at intra-cluster level, in which: in-degree = out-degree centrality;

c. *absorbers* are those firms that absorb more knowledge than they transfer at intra-cluster level, in which: in-degree > out-degree centrality;

d. *isolates* are those firms that are either disconnected or poorly connected at intra-cluster level, so that in-degree = out-degree centrality approximates 0[8].

It is pertinent to add that these indexes have been developed using degree centrality measures and consider those flows of knowledge that directly connect one firm with another. Therefore they don't capture '*liason*' positions characterized by high betweenness centrality but low degree centrality values.

2.3.2. The external openness of the cluster knowledge system

External Openness has been measured considering the knowledge linkages of firms with extra-cluster sources of knowledge. The data collected through questions Q3 and Q4 have been grouped into ten sources and channels of extra-cluster knowledge. The importance of each source for the transfer of technical knowledge into the firm is measured on a 0-3 scale, where 0 stands for 'no importance' and 3 for 'maximum importance'. The final external openness value results from the sum of these ten values.

The degree of interconnection of intra- and extra-cluster knowledge system has been observed considering the presence of t*echnological gatekeepers,* which, consistently with Allen (1997) and Gambardella (1993), correspond to firms that have both high degree of external openness and a high propensity to transfer or exchange knowledge to the other intra-cluster knowledge firms. The

[8] The cut-off values for in-degree and out-degree centrality for being isolated has been conventionally established as [2; 3].

former value has been considered high if it was larger than cluster average[9]. While latter level has been measured considering values for the In-degree/Out-degree ratio lower or equal than 1, which measure firm cognitive positions in the cluster as sources and mutual exchangers (see Section 2.3.1.).

2.3.3. The firm knowledge base

The firm *knowledge base* has been proxied by a principal component analysis of four variables: *three* of them concern the background of technical human resources and *one* is a measure for the degree of experimentation led at firm level.

The emphasis on human resources is justified by a pilot fieldwork that suggested that, in this industry, technical professionals (i.e. oenologists and agronomists) are the drivers of technical change. These can be conceived as 'knowledge workers' since they embody technical knowledge and *own* such an important 'mean of production' upon which the success of the final product is built (Drucker, 1993).

On the basis of this, the analysis looked at: (1) the level of education of professionals (degree, master, PhD); (2) the months of experience in the sector of professionals; (3) the number of firms in which each single professional has been employed previously. At the same time, the author is aware that a set of professionals do not translate immediately into *firms*, which have their own routines, organizational memory and knowledge development activities, that go beyond that of their single human resources. For this reason, the study included a measure of the experimentation carried out within each firm. According to a set of criteria (see Appendix) the experimentation effort was valued on a 0-4 scale.

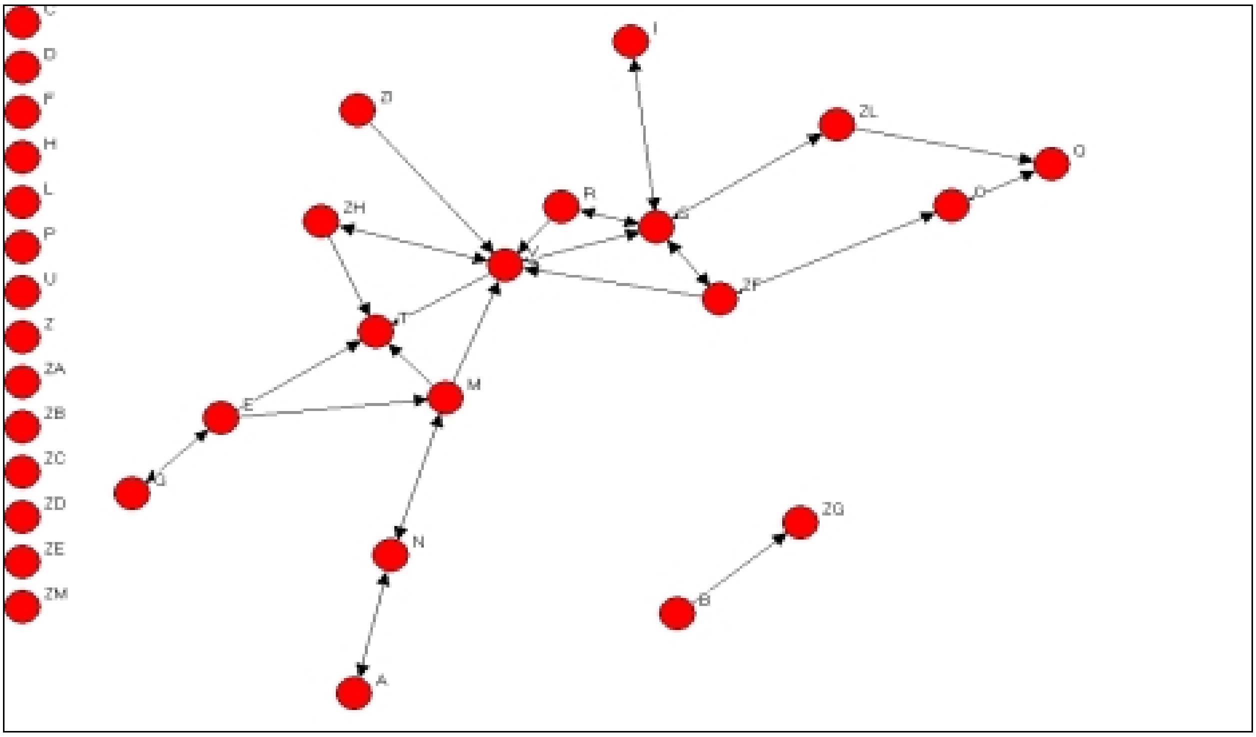
3. COMPARING THE CLUSTER KNOWLEDGE SYSTEMS: EMPRICAL FINDINGS

3.1. Intra-cluster knowledge systems

The comparative study shows that at intra-cluster level, the two wine clusters differ considerably. They differ in terms of both (i) density, (ii) strength of ties and (iii) structural characteristics of the knowledge network. Such differences are perceivable from a preliminary visual inspection of the graphs that represent the two intra-cluster knowledge systems – see Figures 2 and 3 below.

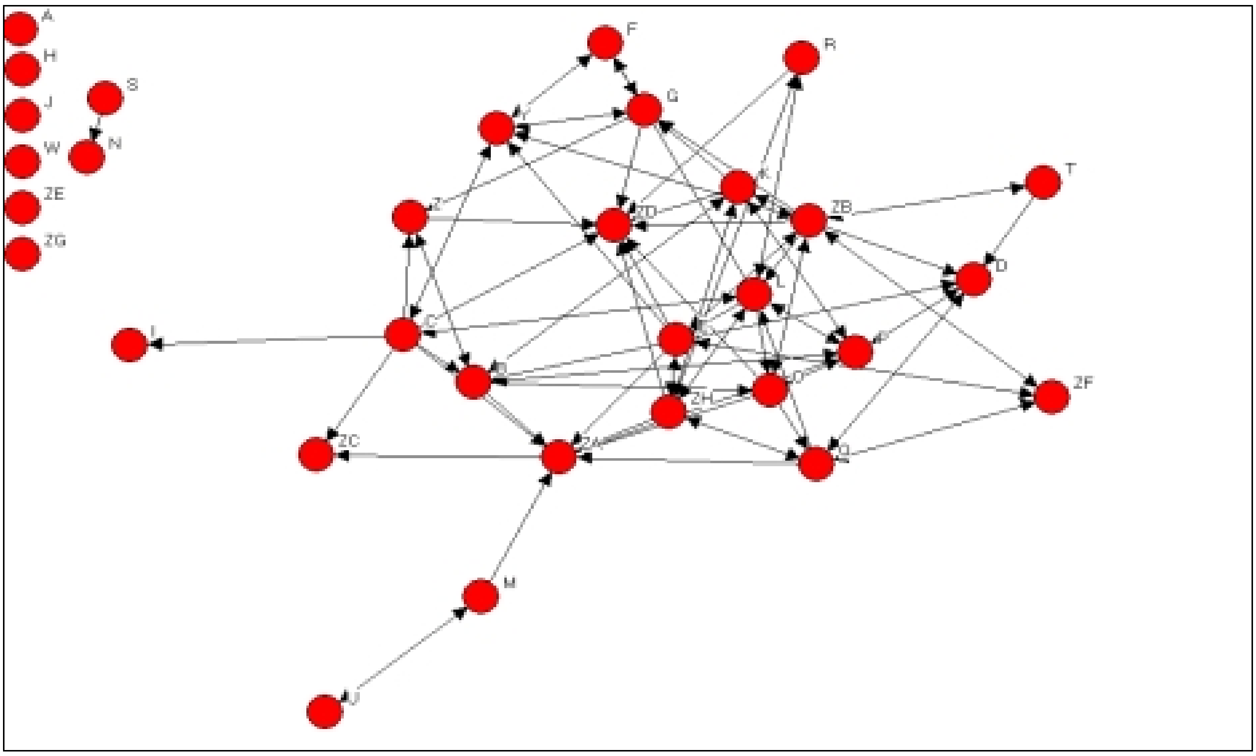
[9] This criteria has the problem of biasing the comparison, as each firm is considered to have higher than average external openness only with respect to *its* cluster average. The alternative option would have been that of considering average external openness of both clusters as a cut-off point. Nevertheless, this would have produced a second bias in de-contextualising the firms from their intra-cluster knowledge system. I therefore opted for the first option.

Figure 2: Intra-cluster knowledge system in Colline Pisane



Note: The positioning of nodes does *not* refer to geographical distances between firms. It is based on a layout with node repulsion and equal edge length bias. The network draws on a directed 32x32 matrix. Linkages represent the existence technical advice knowledge flows between any two nodes considered. The direction of arrows indicate the direction of knowledge flows. Network density: 0.043.

Figure 3: The intra-cluster knowledge system in Colchagua Valley



Note: The positioning of nodes does *not* refer to geographical distances between firms. It is based on a layout with node repulsion and equal edge length bias. The network draws on a directed 32x32 matrix. Linkages represent the existence technical advice knowledge flows between any two nodes considered. The direction of arrows indicate the direction of knowledge flows. Network density: 0.090.

Figure 2 shows the local knowledge system of Colline Pisane. As evident, it is constituted by a main component of interconnected firms and by a numerous set of isolated ones[10]. Figure 3 shows instead that the Colchagua Valley cluster is constituted by a more connected local knowledge system. Beside the minor incidence of isolated firms, even firms that are not isolated seem to interconnect more than those of Colline Pisane.

This is presented analytically by comparing the values of network densities of the two clusters: as shown in Table 3, the cluster of Colline Pisane has a density of linkages that equals 0.043 while the value for Colchagua Valley is about the double (0.090). A density of 0.043 means that each firm, on average, has knowledge linkages with 4.3% of the firms in the cluster. Hence, in Colchagua Valley firms have established on average 9% of total linkages with other firms.

Table 3: Density of the intra-cluster knowledge systems

	Network Density (with isolates)
Colline Pisane	0.043
Colchagua Valley	0.090
Network Density Ratio (Colchagua V./Colline P.)	2.09

Source: Author's own
Note: Network Density represents the percentage of existing linkages on total possible linkages

The density of linkages is a quantitative measure of the knowledge interaction taking place within each of the clusters considered. As such, it does not tell much on the quality, persistence and structure of the knowledge network. Therefore, if considered separately from other indicators, this is not a fully explicative of the "good shape" of an intra-cluster knowledge system.
From a purely descriptive perspective, though, network density shows that firms in Colchagua Valley tend to seek technical advice from other cluster firms more commonly than in Colline Pisane, where this practice seems to be rather limited. It does as well indirectly tell us about the fact that, as shown in Figures above, part of cluster firms in Colline Pisane are not connected at all to the local, intra-cluster knowledge system.

A second relevant element of the intra-cluster knowledge system, is represented by the *strength* of its ties, which relates to the 'quality' and persistence of the knowledge transferred and the 'importance' of the linkages for inducing technical change.

[10] It is worth to remember that isolated nodes represent firms that do not transfer nor receive technical knowledge from any other firms in the cluster.

The two clusters differ considerably also at this respect. Beside being poorly interconnected, the intra-cluster knowledge system in Colline Pisane is mainly characterized by weak linkages. This is represented by the fact that the majority of existing linkages are valued 1 (# 31); while only in three cases linkages have higher strength (see Table 4).

Consequently, in Colline Pisane, the great part of ties do not carry high quality technical knowledge and that knowledge exchange occurs only on an occasional basis[11].

In contrast, in Colchagua Valley ties are stronger and, as shown in Table 4, their average value approaches two. In this case in fact, knowledge linkages tend to be more stable and to carry more fine-grained knowledge, often exchanged to solve specific, complex technical problems.

Table 4: Frequency of knowledge linkages according to strength

	Frequency of ties according to strength			
	Low (1)	Medium (2)	High (3)	Weighted Average
Colline Pisane	31	2	1	1,11
Colchagua Valley	39	29	25	1,85

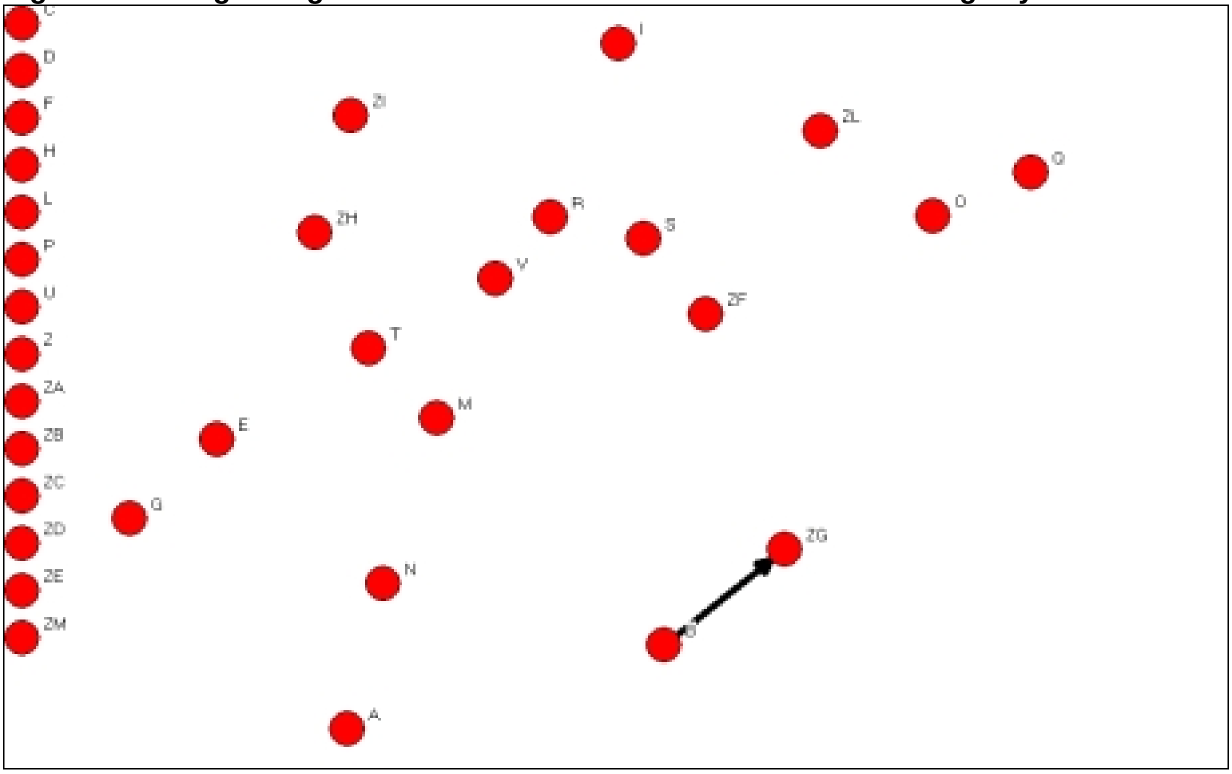
Source: Note: the count of ties has been done considering the number of nodes involved in the relation, therefore a reciprocated tie is counted two.

At a visual inspection, it is possible to observe that in Colline Pisane persistent and high quality knowledge transfer is confined to a dyad of firms (See Figure 4). This suggests that a community of strongly linked professionals and firms is not present in Colline Pisane. The intra-cluster knowledge system is therefore based on a community of firms that occasionally exchange knowledge and technical advice.

Conversely, in the cluster of Colchagua Valley, the major presence of strong and persistent linkages is consistent with the existence of a knowledge community. As shown in Figure below, those firms that are strongly related form a sort of cognitive backbone of the intra-cluster knowledge system (see Figure 5).

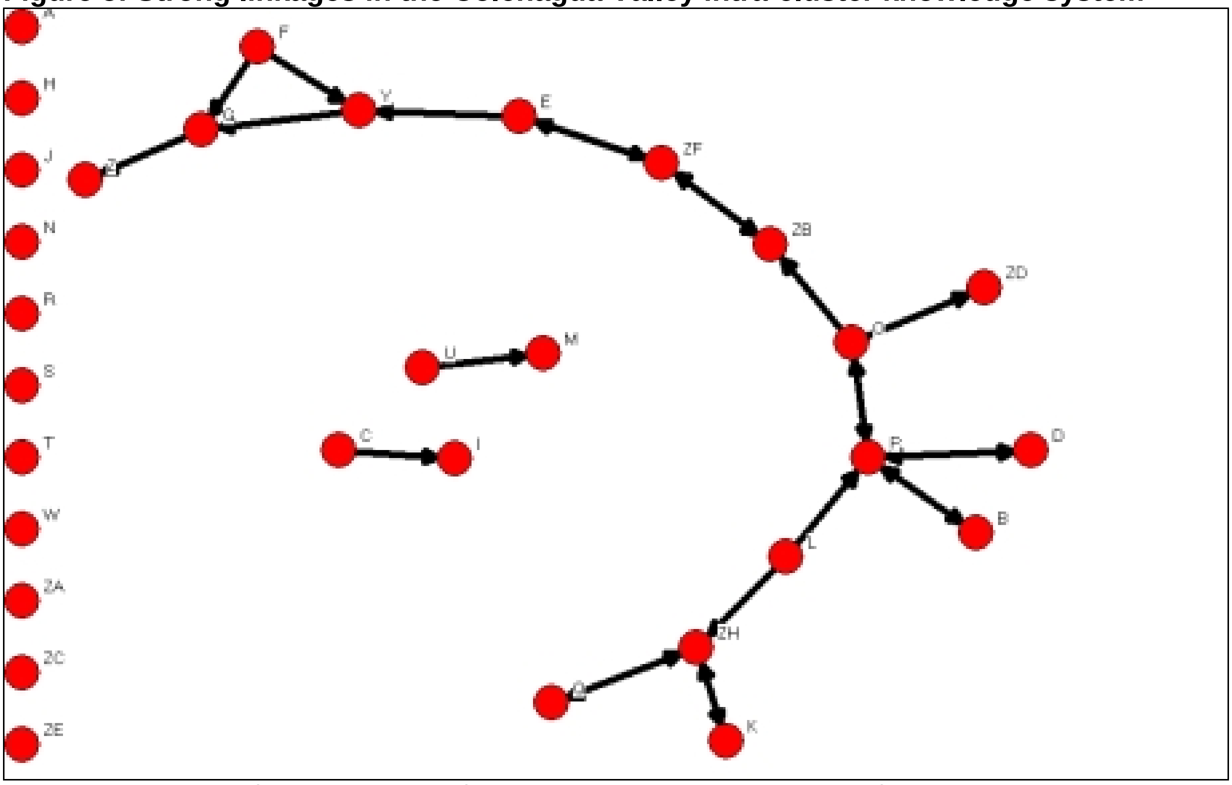
[11] As commented by a respondent during an interview, in the cluster, firms exchange knowledge mainly “every now and then, when they meet in special occasions, such as tasting fairs”.

Figure 4: Strong linkages in the Colline Pisane intra-cluster knowledge system



Note: The positioning of nodes does *not* refer to geographical distances between firms. It is based on a layout with node repulsion and equal edge length bias. The network draws on a directed 32x32 matrix. Linkages represent the existence technical advice knowledge flows valued 3 between any two nodes considered. The direction of arrows indicates the direction of knowledge flows.

Figure 5: Strong linkages in the Colchagua Valley intra-cluster knowledge system



Note: The positioning of nodes does *not* refer to geographical distances between firms. It is based on a layout with node repulsion and equal edge length bias. The network draws on a directed 32x32 matrix. Linkages represent the existence technical advice knowledge flows valued 3 between any two nodes considered. The direction of arrows indicate the direction of knowledge flows.

Finally, in order to describe the intra-cluster knowledge system, I looked at its *structure*. In order to analyze how knowledge flows were structured within the cluster knowledge system, I proceeded through two steps: first, I compared firm *cognitive positions* within clusters and second, I adopted graph theoretical measures for identifying *cognitive subgroups* within the cluster.

As regards the former – *firm cognitive positions* – Table 5 shows a classification of firms according to them behaving as *sources*, *mutual exchangers*, *absorbers* or *isolated* firms. Understandably, the first *three* positions correspond to the most active learning behaviors, because they refer to firms that that transfer, exchange or purely absorb the stock of knowledge available at local level. Interestingly enough, while the majority of them tend to exchange knowledge in a mutual way (e.g. 28% in Colchagua Valley), a minority have imbalanced positions and tend to act either as absorbers of knowledge (6% and 12.5% in Colline Pisane and Colchagua Valley respectively) or as sources of knowledge, as in almost 16% of firms in the Chilean cluster.

Conversely, isolated firms do not play a relevant role in the intra-cluster knowledge system. These have either peripheral positions in the knowledge network or are totally disconnected from it.

Table 5: Firms' cognitive positions in the two clusters

Cognitive positions in the cluster	Colline Pisane	Colchagua Valley
Sources	1 (3%)	5 (15.6%)
- firms with an In/Out degree centrality ratio > 1		
Mutual exchangers	1 (3%)	9 (28.1%)
- firms with an In/Out degree centrality ratio = 1		
Absorbers	2 (6%)	4 (12.5%)
- firms with an In/Out degree centrality ratio < 1		
Isolates	28 (87.5%)	14 (43.7%)
- firms with In and Out centralities approximating to 0		

Source: Author's own

It is interesting to notice that this latter cognitive position accounts for a highly significant number of firms in both clusters. In Colline Pisane, the percentage of isolates equals 87.5% of total firms[12], while only a small percentage of firms seem to play the active roles of sources and mutual exchangers of knowledge (3% each). A slightly better figure emerges form the case of Colchagua Valley, where isolates account for 43.7% of firms.

[12] This percentage refers to the definition of isolates provided in Section 2.3.1. and thus it does not fully coincide with pure isolated firms in sociometric terms (i.e. not connected firms).

As concerns latter point – *cohesive subgroups* – the two clusters present quite different structures. The cluster of Colline Pisane, as shown in the previous paragraphs, is characterized by a highly disconnected local knowledge system with the exception of one main component that characterizes for being a weak intra-cluster knowledge network with a cliquish shape. In fact, the analysis of cohesive subgroups detected five *weak* cliques[13] and one *2*-clique. All weak cliques are formed by number of three firms while the *2*-clique includes five firms. A meaningful interpretation of this result is that knowledge tends to flow within highly restricted sub-groups of firms, which are partially overlapping and therefore connected by few key firms in the component (i.e. members of one clique are also members of one or more other cliques).

Table 6 shows the degree of cliques' overlapping. The table indicates the number of firms that participate in more than one of the sub-groups identified.

Table 6: Cohesive subgroups in Colline Pisane: degree of overlapping cliques and 2-cliques

	Clique 1	Clique 2	Clique 3	Clique 4	Clique 5	2-Clique
Clique 1	-	2	1	1	0	1
Clique 2	2	-	1	1	0	2
Clique 3	1	1	-	2	2	0
Clique 4	1	1	2	-	1	0
Clique 5	0	0	2	1	-	0
2-Clique	1	2	0	0	0	-

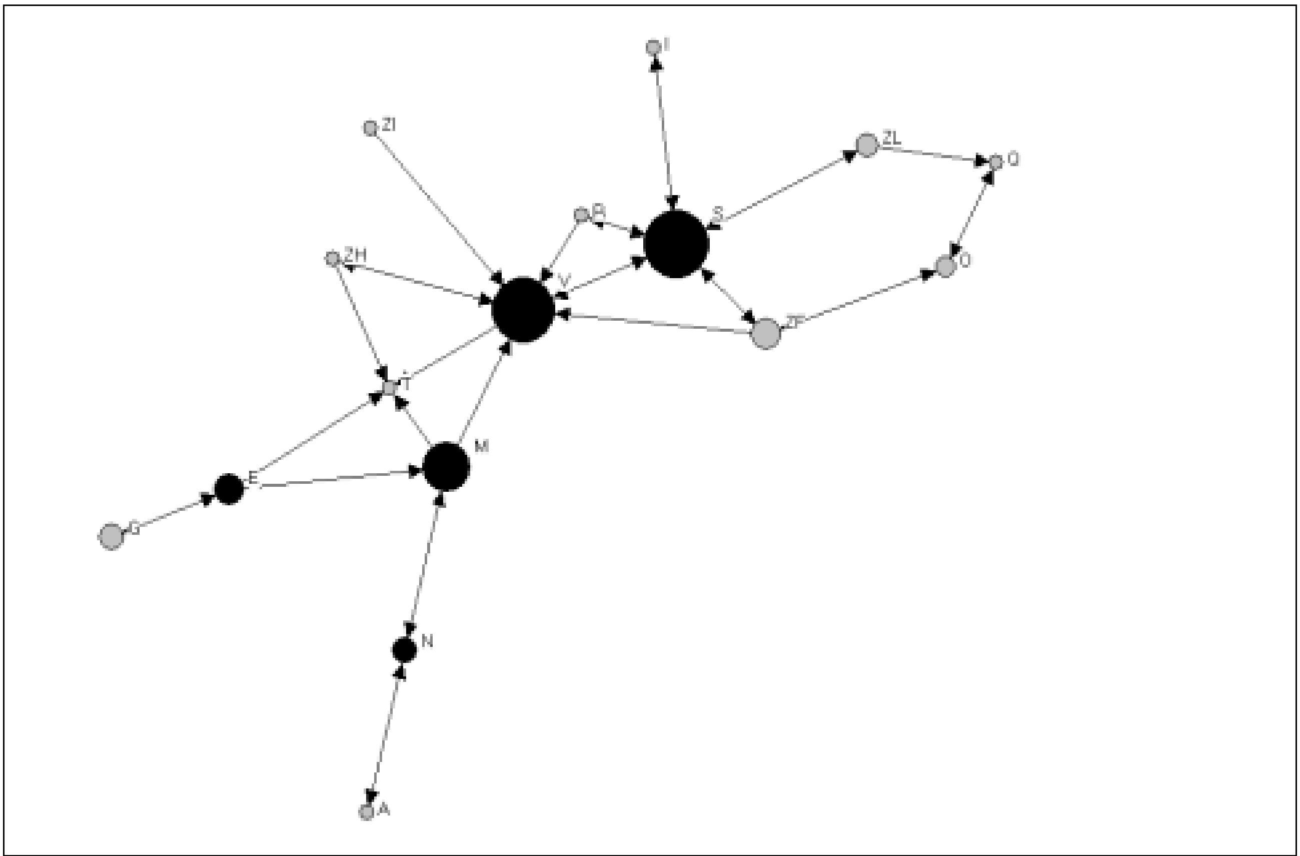
Note: Each cell indicates the number of firms that participate in the both the cliques indicated in the row and column of the table. As an example, Clique 1 and 2 have 2 firms overlapping.

Quite understandably, the firms that participate in more than one sub-group coincide with (i) the network *cutpoints* and (ii) the firms with higher *betweenness* centrality. This means that these firms are both essential to (i) keep the existing network connected and to (ii) connect distant firms.

These firms are visible in Figure 6 below: darker nodes represent the cutpoints while the size of firms is proportional to their betweenness centrality value – see Figure 6. This has to say about the vulnerability of the intra-cluster knowledge system, which appears weakly anchored to few cutpoint firms. This knowledge structure seems therefore highly liable to disruption, in case in which the cutpoint firms exit the industry or decide to disconnect entirely from the local cluster.

[13] Scott (2000) defines *weak cliques* 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.

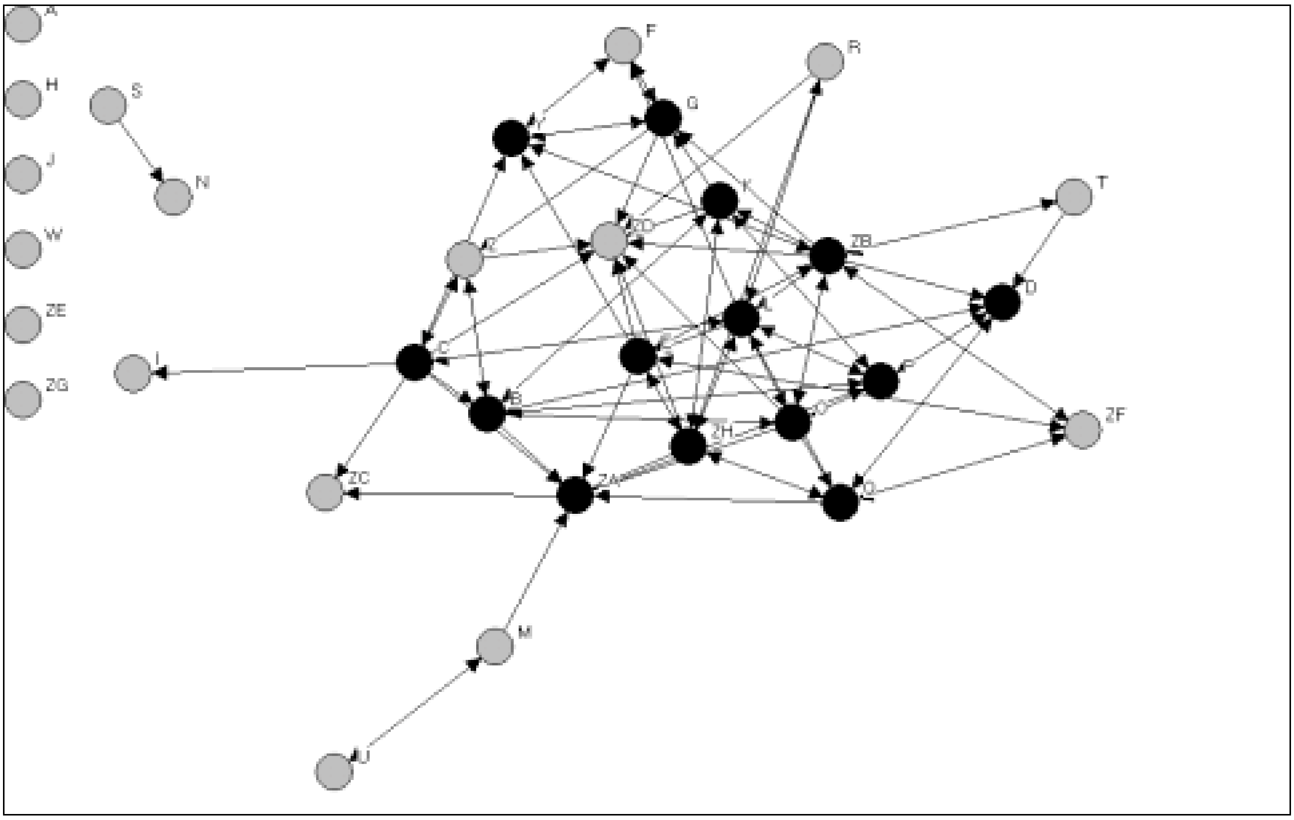
Figure 6: Cohesive subgroups in Colline Pisane



Note: The positioning of nodes does *not* refer to geographical distances between firms. It is based on a layout with node repulsion and equal edge length bias. The network draws on a directed 32x32 matrix. Linkages represent the existence technical advice knowledge flows between any two nodes considered. The direction of arrows indicate the direction of knowledge flows. Dark nodes indicate cutpoints and size of nodes is proportional to betweenness centrality.

The case of Colchagua Valley is considerably different from the previous one. The local knowledge system is more complex and shows a typical *core-peripheral* pattern of knowledge exchange (Borgatti, Everett, 1999). This means that there is a subgroup of firms in the network that is highly interconnected and constitutes the cognitive *core* of the local system, while the firms that gravitate around the core form part of a *periphery*. Firms in the core tend to be highly interconnected among them; instead, peripheral firms tend to establish loose linkages with the core firm and not to interconnect with other peripheral firms (see Figure 7).

Figure 7: Core-peripheral relations in Colchagua Valley



Note: The positioning of nodes does *not* refer to geographical distances between firms. It is based on a layout with node repulsion and equal edge length bias. The network draws on a directed 32x32 matrix. Linkages represent the existence technical advice knowledge flows between any two nodes considered. The direction of arrows indicates the direction of knowledge flows. Dark nodes represent core firms, light nodes peripheral ones.

More specifically, as shown in Table 7, the density of these four types of relations, namely: core-to-core (top left), core-to-periphery (top right), periphery-to-core (bottom left) and periphery-to-periphery (bottom right) vary in each case[14]. It is higher for core-to-core relations (0,571), which means that core firms tend to transfer knowledge more often within the core. Core firms are also sources of knowledge for peripheral firms (core-to-periphery density is 0,155) but this relation is much looser than the previous one. At the same time, core firms tend not to receive knowledge from peripheral firms (periphery-to-core density is very low 0,083) and even less do peripheral firms transfer or receive knowledge from other peripherals (periphery-to- periphery density is 0,026).

[14] For core/periphery analysis I adopted a directional dataset.

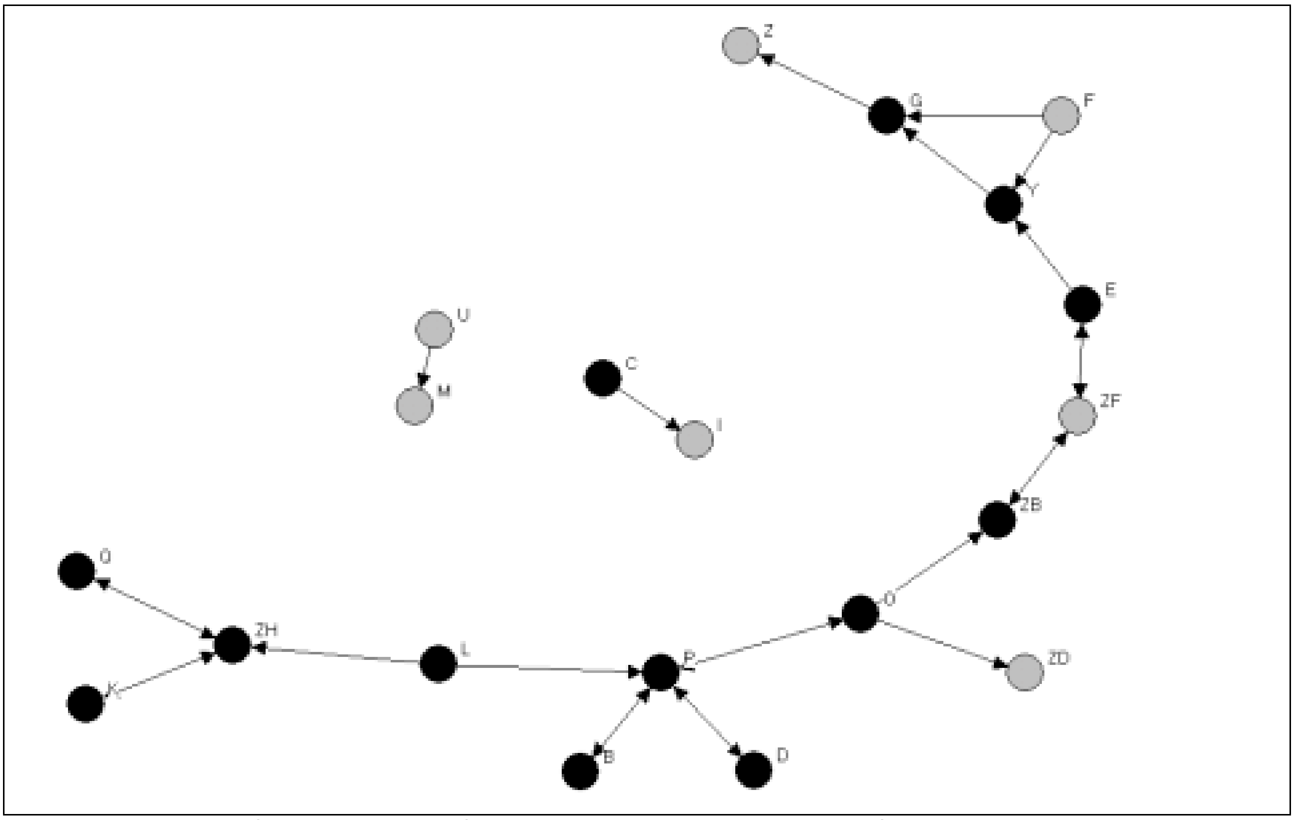
Table7: Cohesive subgroups in Colchagua Valley: a core-periphery structure

	The Density of Linkages (Knowledge transfer from row to column)	
	Core	Periphery
Core *(n_C=14)*	0.571	0.155
Periphery *(n_P=18)*	0.083	0.026

Source: UCINET 6 applied to author's own data. The density has been calculated on a valued directed dataset

Interestingly enough, the majority of firms that constitute the strongly connected community of firms (shown in Figure 5) form also part of the core. This further supports the idea of the core being a community of both densely and strongly interconnected firms (see Figure 8).

Figure 8: Core-periphery and strong community in Colchagua Valley



Note: The positioning of nodes does *not* refer to geographical distances between firms. It is based on a layout with node repulsion and equal edge length bias. The network draws on a directed 32x32 matrix. Linkages represent the existence technical advice knowledge flows between any two nodes considered. The direction of arrows indicates the direction of knowledge flows. Only linkages with value 3 are considered in the Figure. Dark nodes represent core firms, light nodes peripheral ones.

If compared to Colline Pisane, then, the core-peripheral network observable in Colchagua Valley appears to be a more advanced knowledge structure, for two sets of reasons: on one hand because there is an intense exchange of knowledge within the core. Core firms, in fact, are all linked together by the local community of professionals, potentially creating an intra-core, self-reinforcing environment of collective learning; on the other hand, core firms represent important sources of technical knowledge for peripheral firms. Therefore, instead of being totally disconnected, as occurs in Colline Pisane, peripheral firms expose themselves more often to leakages of knowledge from the core.

3.2. The extra-cluster knowledge systems and knowledge percolation into the local cluster

The external sources of knowledge are primarily constituted by: private consultants, suppliers research institutes and universities and business associations (see Table 8). More specifically, while both clusters appear to be highly interconnected with private consultants[15], firms in Colchagua Valley have a higher propensity to co-operate with research institutes than firms in Colline Pisane. In the latter case, in fact, only 28% of respondents declare of benefiting of the transfer of technical knowledge from such institutions. This percentage is considerably higher (69%) in the Chilean case, where industry-university linkages appear to be more frequent. Suppliers of inputs are equally important in the two clusters since around 60% of the firms name them as sources of knowledge. Finally, business associations seem to play a relevant role in technology transfer only in the Chilean case.

Table 8: Sources of extra-cluster knowledge and external openness

	% of firms with at least one knowledge linkage with:				**External Openness**
	Research Institutes	Suppliers	Consultancies [domestic; foreign]	Business Associations	
Colline Pisane	28%	56%	97% [97%; 0%]	3%	3.4
Colchagua Valley	69%	60%	97% [69%; 53%]	56%	7.4

Source: Author's own

Hence, firms in Colchagua Valley are more interconnected to extra-cluster sources of knowledge, than firms in the Italian cluster. The average value for 'external openness' is in fact 7,4 and 3,4 respectively[16]. But for a cluster to absorb knowledge it is also important that those firms with higher

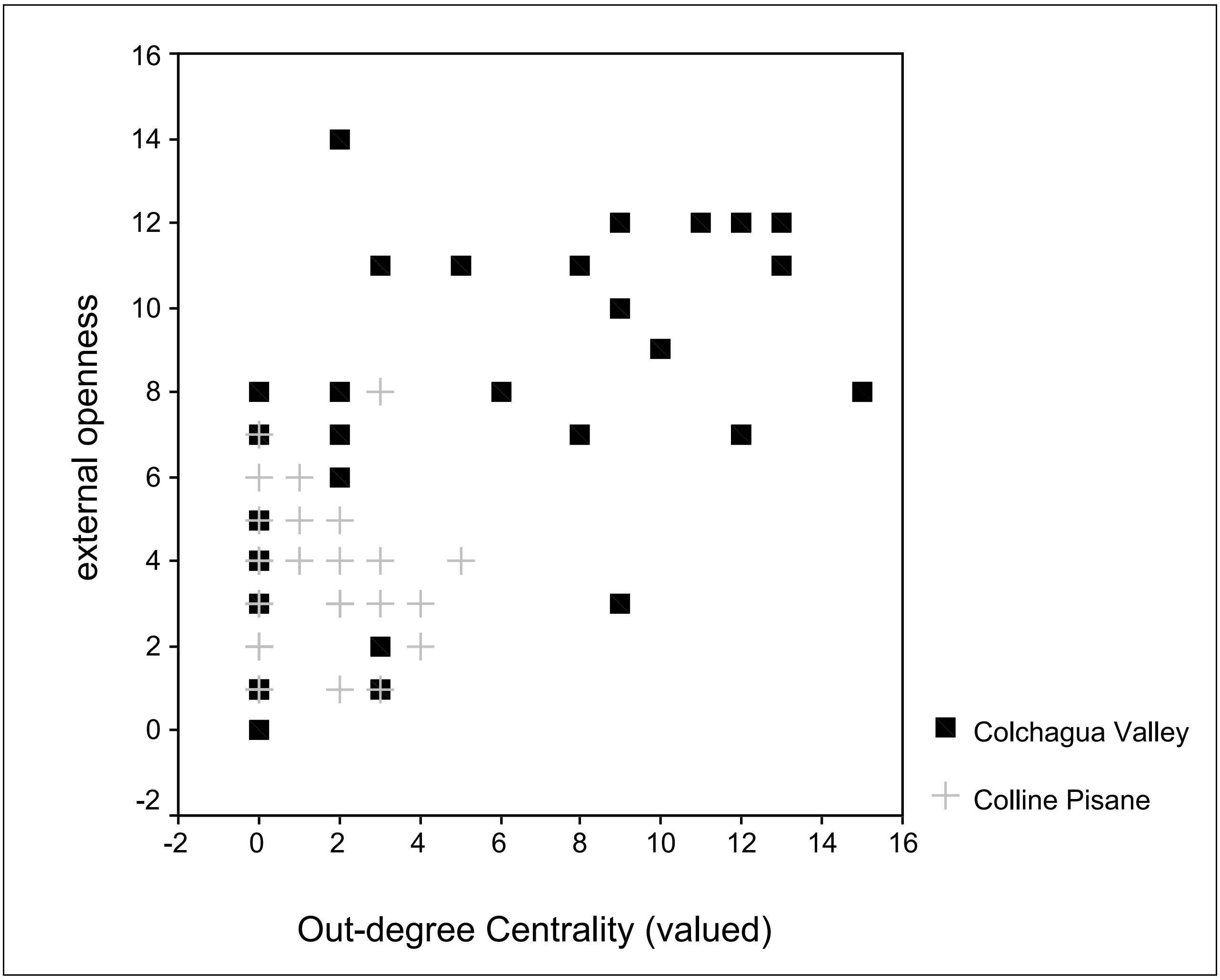
[15] However, firms in Colline Pisane tend to hire domestic consultants, while firms in the Chilean case have stronger linkages with international consultants, typically French, Australian, South African or Californian.

[16] This result clashes with the view of advanced countries having stronger national innovation systems.

external openness allow the acquired knowledge to percolate into the intra-cluster knowledge system. For this to happen, it is necessary that firms with higher external openness are also local sources or exchangers of knowledge and behave as technological gatekeepers accordingly. So how do the clusters differ at this respect?

To start with, Figure 9 plots the values of external openness and out-degree centrality for the two clusters. Black squares represent firms in Colchagua Valley, while gray crosses mark those of Colline Pisane. Quite consistently with the above presented external openness records, the latter firms are mainly concentrated in the lower left hand side of the chart, while firms in Colchagua Valley tend to occupy the other side of the quadrant, showing higher values for both indexes.

Figure 9: External Openness and Out-degree centrality: visualizing the two clusters



Note: The scale for external openness ranges from a mimimum of 0 (no extra-cluster knowledge linkages) to a maximum of 30 (maximum interconnection with all categories of knowledge sources). The scale for out-degree centrality ranges from 0 (no linkages at intra-cluster level) to 31 (maximum number of linkages possible; n-1).

These results suggest preliminarily that there is higher likelihood of technological gatekeeping behaviours being present in Colchagua Valley than in Colline Pisane. More analysis, which matches cognitive positions – i.e. firms being local sources or mutual exchangers – and external openness values, has given the following results:

Table 9: Identifying technological gatekeepers

	Colline Pisane		**Colchagua Valley**	
	Total	*> EO (*)*	*Total*	*> EO(*)*
Sources - firms with an In/Out degree centrality ratio > 1	1	0	5	5
Mutual exchangers - firms with an In/Out degree centrality ratio = 1	1	0	9	6
Total	*2*	*0*	*14*	*11*

Note: (*) represents the number of firms that have higher than average external openness. External openness is considered relative to each cluster.

As Table 9 shows, about one third of firms in the Chilean cluster behave as technological gatekeepers, while no firm play such a role in Colline Pisane. Hence, the former cluster has a higher capacity of absorbing extra-cluster knowledge.

3.3 A synthesis of results and new open issues

The analysis carried out so far can be summarised considering Colchagua Valley as a more *learning-rich* cluster environment, while the Colline Pisane could be classified as a *slow-learner*. This study does not explicitly address the issue of knowledge generation (i.e. innovation) so I will just concentrate on the intra-cluster learning process and that of the absorption of extra-cluster knowledge. At this respect, it is clear that Colline Pisane is far weaker if compared to Colchagua Valley where, in relative terms, there is more going on. More explicitly, the case of Colchagua Valley seems one where a group of professionals is present, which has given rise to a *learning-intensive* knowledge community.

Hence, while the first cluster shows a disruptive path of learning, characterised by a vulnerable knowledge system, the second case manifests a higher degree of connectivity, but where knowledge distributes in a very *uneven* way, following a pattern of knowledge cohesion and exclusion. Hence, even this case is far from the idealised idea of collective learning, where firms *all* participate to the improvement of local stocks of knowledge and knowledge is in the air. More realistically, learning seem to occur within a restricted subset of firms (i.e. the core) while the rest of firms tend to be excluded from the intra-cluster learning processes.

Issues concerning the explanation and functioning of a core/community behaviour – i.e. the theoretical interpretations of how and why it comes into being, evolves, changes and/or degenerates – are not directly explored in this paper, so I will draw on existing literature to make an interpretation for it. Of particular relevance is the literature that explains these phenomena at inter-organizational level (e.g. von Hippel, 1987; Carter, 1989; Appleyard, 1996; Schrader, 1991; Powell et al., 1996). Consistently with the story presented here, those studies suggest that the horizontal information trade between potentially rival firms should not be viewed as a random leakage of non-appropriable knowledge (Mansfield, 1985), but rather as a profit-seeking decision of economic agents that release knowledge on the expectancy that they will be reciprocated (benefit) *and* do so under the condition that it won't generate a "competitive backlash" (cost) for the releasing firm (Carter, 1989). This literature suggests that exactly because the releasing firms expect to be reciprocated, they tend to transfer knowledge to those alters that seem likely to do so (Schrader, 1991). Other contributions stress the fact that knowledge transfer is more likely to take place when firms have complementary and overlapping knowledge endowments (e.g. Rogers, 1983; Lane, Lubatkin, 1998). It seems therefore that a tension between proximity and diversity in firm knowledge bases exists, which shapes the propensity of individual firms to release proprietary knowledge or ask for advice.

In this paper I won't explore this tension further. What I will do though is to draw from these considerations and explore whether firm knowledge bases shape the cluster knowledge system.

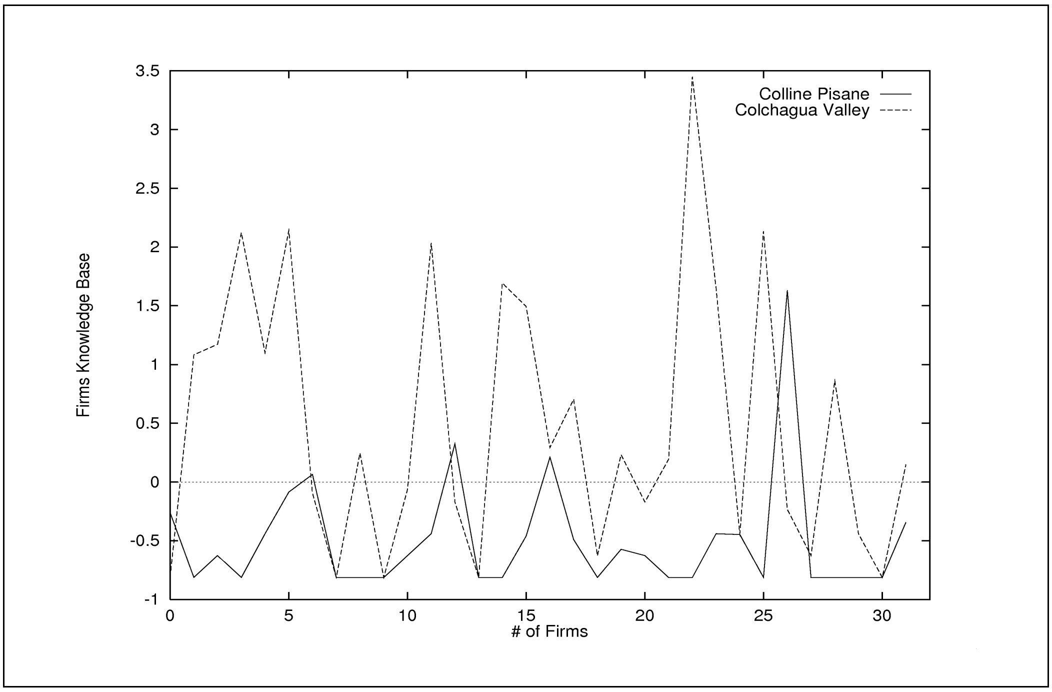
4. LINKING CLUSTER KNOWLEDGE SYSTEMS WITH FIRM KNOWLEDGE BASES

4.1. Heterogeneity of firm knowledge bases

A second objective of this paper was that of exploring the relation between the firm knowledge base and the characteristics of the cluster knowledge networks. A starting point at this respect is to analyze if and how much firm knowledge bases vary both within and across clusters.

As Figure 10 shows, firm knowledge bases in the Italian cluster are comparatively inferior to those of the Chilean cluster. The plot also highlights the higher heterogeneity within the second cluster, while in Colline Pisane firms have similarly low knowledge bases. This is made evident by the average value of the knowledge base factor, which is 0.49 in Colchagua Valley and - 0.49 in Colline Pisane and by its standard deviation, which is 1.12 in the former cluster and 0.50 in the latter (Table 10).

Figure 10: A comparison of firms' knowledge bases in the two clusters



Source: Author's own

This gap is due to differences in both human resources and experimentation intensity. In fact, in Colchagua Valley, firms employ, on average, *better educated technical personnel*: each firm employs more than two employees (2.9) holding a degree or upper qualification [master, doctorate] in technical fields. The value for Colline Pisane is 1.33, which means that one out of three firms have on average only one technical graduate fully employed within the firm. In addition, professionals differ in terms of past working experience in the sector. In fact, in Colchagua Valley, professionals have longer previous experiences (164 months *per firm*) than those employed in Colline Pisane (28.6 months *per firm*). Furthermore, professionals in the Chilean case seem also more dynamic in terms of labour turn over and have, on average, been employed by different wine producers within the country and abroad considerably more than those of Colline Pisane.

More importantly, the Chilean firms of Colchagua Valley perform more in-house experimental activities, than the Italian firms of Colline Pisane. The average value is in fact 1.59 and 0.69 respectively: in Chile, about half of the firms in the cluster leads experimentation in both the vineyard and cellar and eighty percent of them practice at least some form of experimentation. In contrast, in the Italian case, about sixty percent of firms do *not* practice any form of experimentation.

Table 10: Differences in firm knowledge bases across the two clusters

	Colline Pisane	Colchagua Valley
Average firm knowledge base	-0.49	0.49
Standard deviation	0.50	1.12
Firms that employ full time at least one technical professional (in percentage values)	28%	72%
Among those that employ technical professional:		
Average number of professional (per firm data)	1.33	2.9
Average months of experience of professionals (per firm data)	106	218.6
Average number of firms previously employed (per firm data)	4.2	8.3
Percentage of firms that experiment on total	31%	72%
Average experimentation intensity	0.7	1.6

Source: Author's own

4.2. Firm knowledge base and shape of cluster knowledge system: testing hypotheses

To investigate whether firms with different knowledge bases relate with the characteristics of the cluster knowledge systems, I looked for the correlation between the degree of advancement of firm knowledge bases – measured by their factor values – and the different indicators of both intra- and extra-cluster connectivity. Hence, I run a non-parametric correlation between firm knowledge bases and these connectivity indicators, namely: *in-degree* and *out-degree centrality* for intra-cluster connectivity and *external openness* for extra-cluster connectivity. Results are shown in Table 11 below.

Table 11: Non-parametric correlations between firm knowledge base and connectivity

	Out-degree Centrality (dic.)	Out-degree Centrality (val.)	In-degree Centrality (dic.)	In-degree Centrality (val.)	External Opennes
Kendall's tau_b (Correlation Coefficient)	0.422**	0.438**	0.427**	0.393**	0.539**
Sig. (1-tailed)	.000	.000	.000	.000	.000
N	64	64	64	64	64

** Correlation is significant at the .01 level (1-tailed).

The analysis shows that there is a statistically significant correlation between all the indicators considered and the values of firm knowledge base – thus verifying both hypotheses (1a) and (1b). This implies that the capacity of firms of cognitively interconnecting both with intra- and extra-cluster sources of knowledge is related to their knowledge bases. All correlations are positive, meaning that the higher the knowledge base of firms, the higher their likelihood of transferring and absorbing knowledge both at intra- and extra-cluster levels. Among these, the highest correlations are between firm knowledge base and external openness [Kendall tau_b = 0.54] and also between the former and out-degree centrality [Kendall tau_b = 0.42 and 0.44 for dichotomous and valued data respectively].

This suggests that firm knowledge base influences the propensity of firms to both absorb extra-cluster knowledge and to transfer knowledge to other local firms, behaving as technological gatekeepers.
As for the in-degree centrality, the correlations are weaker, but still significant, which might imply that at lower levels of knowledge base, firms might be linked to the local knowledge system as absorbers of knowledge rather than sources, provided, for example, that a *minimum* knowledge base threshold is reached.

CONCLUSIONS

This study addressed two types of issues: one aimed at showing whether there were differences in the knowledge systems of two clusters at different stages of development. The second was interested in shedding light on the relation between the degree of advancement of firm knowledge bases and the difference of cluster knowledge systems.

As concerns the first issue, this paper does show that these two clusters have different knowledge systems. The interesting aspect is that these are not merely *different* but that one seems to be *better* than the other in terms of density, strength of ties, cohesiveness and external openness. And this corresponds to the dynamic emerging cluster – Colchagua Valley. Although the study was not designed to provide a dynamic interpretation of clusters and knowledge networks co-evolution processes, it shows at least that a relation between these two dimensions is plausible and therefore deserves further investigation.

Furthermore, these empirical results do not support the idea that clusters are locus of innovation, where knowledge diffuses randomly in the air and generates a collective learning environment. On the contrary, most empirical evidence goes in the opposite direction, showing that only a small subset of firms actively participate in the knowledge diffusion process at intra-cluster level and in the absorption of extra-cluster knowledge, while the bulk of firms are either peripheral or totally disconnected from the intra-cluster knowledge system. This is particularly true when firm knowledge bases are very low as for the Colline Pisane case, where beside low degree of intra-cluster connectivity, firms tend to be more isolated from extra-cluster knowledge sources, thus generating the ideal environment for negative lock-in to occur.

This spurs the conclusions further by showing that a relation exists between micro-level knowledge endowments and the structural characteristics of the cluster knowledge system. The significance of statistical correlation tests in Section 4.2. clearly suggests that advances in firm knowledge bases and connectivity both at intra- and extra-cluster level go in the same direction, at least in the emerging phase of the cluster development path.

These results hint some implications on the role of clusters for innovation. They suggests that clusters are not necessarily “beautiful” and should not be conceived as places where, to use Porter’s words: “proximity increases the speed of information flow within the national industry and the rate at which innovations diffuse.” (Porter 1990: 157) and where “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’.” (Porter, 1990: 156). Instead, I have presented here a story where connectivity and cluster learning and absorptive capacity is an outcome that depends on the nature of micro units, whose relation with meso-level structural characteristics has just started to be understood.

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Appendix

A: Sociometric measures

A.I. Network Density. The density of a graph is measured by the ratio of the number of lines present in the graph to the maximum possible.

A.II. Clique and 2-cliques: a **clique** in a graph is a maximal complete subgraph of three or mode nodes. It consists of a sub-set of nodes all of which are adjacent to all of the members of the clique. In a graph we can have more overlapping cliques. A ***n*-clique** is a maximal subgraph in which the largest geodesic distance between any two nodes is no greater than *n*. Hence a 2-clique is a subgraph in which all members need not to be adjacent but are reachable through at most one intermediary.

A. III. Core/Periphery Models are based on the notion of a two-class partition of nodes, namely, a cohesive subgraph (the core) in which nodes are connected to each other in some maximal sense and a class of nodes which are more loosely connected to the cohesive subgroup but lack any maximal cohesion with the core. The analysis sets the density of the core to periphery ties in an ideal structure matrix. The density represents the number of ties within the group on total ties possible.

A.IV. Degree centrality depends on the links that one node has with the other nodes of the network. It is a simple measure because it counts the direct ties with other nodes. It can be calculated both for undirected and directed graphs. In this study, both in-degree and out-degree centrality are used. In-degree counts the number of ties incident to the node; out-degree centrality the number of ties incident from the node.

$C_D(n_i) = d(n_i)$
where $d(n_i)$ is the sum of the nodes adjacent to that node.

A.V. Cutpoint. A node n_i is a cutpoint if the number of components in the graph that contains n_i is fewer than the components in the subgraph that results from deleting ni from the graph.

A.VI. Actor betweenness centrality is a measure of centrality that considers the position of nodes in-between the geodesic (i.e. shortest path) that link any other node of the network.
Let g_{jk} be the proportion of all geodesics linking node j and node k which pass through node i, the betweenness of node i is the sum of all g_{jk} where i, j and k are distinct.

$C_B (n_i)= \sum_{j<k} g_{jk} (n_i)/ g_{jk}$

This index has a minimum of zero when n_i falls on no geodesics and a maximum which is (g-1) (g-2)/2 (g=total nodes in the network) which is the number of pair of nodes not including n_i.

B: Firm knowledge base

Knowledge base has been measured by applying a Principal Component analysis to the following four correlated variables:

Variable 1: Human Resources
This variable represents the cognitive background of each firms' knowledge skilled workers on the of their degree of education. According to previous studies regarding returns to education, we assume that the higher the degree of education the higher is their contribution to the economic returns of the firm. On this assumption we weight each knowledge skilled worker differently according to the degree attained so that:

Human Resource = 0.8* Degree + 0, 05* Master + 0,15* Doctorate

A weight of 0.8 has been applied to the number of graduate employees in the firm which include also those that received higher levels of specialisation. In such cases the value adds up a further 0.05 times the number of employees with masters and 0.15 for those that have a Ph.D.
Only degrees and higher levels of specialisation in technical and scientific fields related to the activity of wine production (i.e agronomics, chemistry, etc.) are taken into account.

Variable 2: Months of experience in the wine sector
This variable has been included as it represents the cognitive background of each of the abovementioned resources in temporal terms. Time is in fact at least indicative of the fact that accumulation of knowledge has occurred via 'learning by doing' (Arrow, 1962). More in detail, the variable is the result of a weighted mean of the months of work of each knowledge skilled worker in the country and abroad:

Months of Experience in the Sector= 0,4* n° months (national)+ 0,6* n° months (international)

To the time spent professionally abroad we attributed a higher weight because the diversity of the professional environment might stimulate an active learning behaviour and a steeper learning curve. The learning experiences considered are those realised in the wine industry only.

Variable 3: Number of firms in which each knowledge skilled worker has been employed
This variable includes the professional experience in other firms operating in the wine industry. Also in this case we weighted differently national and international experiences, giving to the latter a higher weight.

Number of Firms= 0,4*n° firms (national)+ 0,6* n° firms (international)

Variable 4: Experimentation
In this case, the level of experimentation at firm level has been calculated according to the following scale:

(0) for no experimentation;
(1) when some form of experimentation is normally carried out but only in one of the activities of the productive chain (either in viticulture or vinification);
(2) when is led in at least two activities of the productive chain (normally in both viticulture and vinification);
(3) when at least two activities of the productive chain are marked and the firm has been engaged in one joint research project with a university or a research lab in the last 2 years.
(4) when at least two activities of the productive chain are marked and the firm has been engaged in more than one joint research project with a university or a research lab in the last 2 years.

Principal Component Analysis extracted one component, which I adopted as a measure of knowledge base.