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By

Elisa Giuliani
Facultà di Economia
University of Pisa
Via Ridolfi 10
56124 Pisa (Italy)

&

SPRU,
University of Sussex
Falmer, Brighton
BN1 9QE (UK)

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NETWORK DYNAMICS IN REGIONAL CLUSTERS:

A NEW PERSPECTIVE FROM AN EMERGING ECONOMY

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Facultà di Economia
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Abstract

Regional clusters are spatial agglomerations of firms operating in the same or connected industries, which enable innovation and economic performance for firms. A wealth of empirical literature shows that one of key elements of the success of regional clusters is that they facilitate the formation of local inter-organizational networks, which act as conduits of knowledge and innovation. While most studies focus on the benefits and characteristics of regional cluster networks and focus on advanced economies and 'hot spots', this paper advances with the existing literature by analyzing network dynamics and taking an emerging economy's perspective. Using longitudinal data of a wine cluster in Chile and stochastic actor-oriented models for network dynamics, this paper examines what micro-level drivers influence the formation of new knowledge ties among wineries. It finds that cohesion effects (reciprocity and transitivity) as well as firm-level heterogeneity in the knowledge bases influence the evolution of the knowledge network. Next, it explores how these micro-level network drivers influence the macro-level structural evolution of the local knowledge network. Empirical results have interesting implications for the cluster competitiveness and network studies literatures and the burgeoning literature on corporate behavior in emerging economies.

1. Introduction

It is generally acknowledged that regional clusters enable superior innovation and economic performance for firms. This was first documented by Alfred Marshall (1920) writing about industrial districts, and supporting evidence was accumulated throughout most of the past and present centuries (among many others: Allen, 1983; Piore and Sabel, 1984; Aydalot and Keeble, 1988; Pyke et al., 1990; Becattini, 1991; Krugman, 1991; Audretsch and Feldman, 1996; Storper, 1997; Scott, 1998; Lawson and Lorenz, 1999; Baptista, 2000; Cooke, 2001; Capello and Faggian, 2005). For organization and management scholars, the most influential contributions raising consciousness about the importance of location for firm competitiveness are probably Saxenian's (1994) book on Silicon Valley, and Michael Porter's (1990, 1998) works on clusters and competitiveness. Interest in regional clusters is evident in the conceptual models aimed at understanding cluster governance (Bell et al., 2009; Arikan, 2009) and the factors shaping their evolution (Pouder and St. John, 1996; Romanelli and Khessina, 2005; Mesquita, 2007).

In spite of this long-standing and vast literature, debate about what is so special about regional clusters is still open. A central tenet of contemporary studies on regional clusters is that geography *per se* does not guarantee firm success (see e.g. Boschma, 2005; Tallman and Phene, 2007) and that it is the social networks that are generated across cluster organizations that explain at least part of their innovativeness (Owen-Smith and Powell, 2004; Smith-Doerr and Powell, 2005; Singh, 2005). As Gittleman (2007) and Giuliani (2007) suggest, the benefits of spatial proximity for innovation do not spring from unplanned, random interactions – the Marshallian metaphor of "knowledge in the air" - but rather are based on purposeful and selective social and professional contacts and informal communications among employees within local social networks that enhance innovative performance. A recent study by Whittington et al. (2009, p. 117) on the US biotechnology industry confirms this, showing that "both geographic and relational conceptions of location matter for innovation, but…., *networks are primary*" (emphasis added). Networks act as channels of knowledge, which can be used and recombined at firm level to generate innovative processes and products.

Firms in regional clusters use diverse type of networks to access knowledge from local and distant actors. Distant ties are important to increase the variety of knowledge sources for the local context and to avoid the cluster formation from becoming a technology trap. Local ties, which are the focus of this paper, bring other benefits. First, they are typically high value in terms of the quality of the knowledge they channel, which is often rich, fine-grained and tacit – i.e. "capable of transmitting subtle cues" (Bell and Zaheer, 2007, p. 957). The richness derives from the geographical proximity of managers and workers who are able to meet face to face to discuss problems. Ambiguous and uncertain problems are more easily resolved through direct observation and confrontation. Second, workers operating in similar environments are likely to encounter context-specific problems and are more able to develop the expertise required to resolve them. The recombination of local skills and knowledge through social networking enables unique solutions, which in many cases are at the basis of firms' product differentiation and innovation strategies. Thus, the embeddedness of firms in local social networks is considered crucial for their upgrading and innovativeness (Bell, 2005; Gittleman, 2007; McDermott et al., 2009; Perez-Aleman, 2010).

Notwithstanding the widespread consensus about the importance of networks for promoting innovation in regional clusters, research in this area suffers from two limitations. First, most studies focus on the benefits and characteristics of regional cluster networks but seldom analyze their dynamics. A conventional understanding is that networks in regional clusters are dense and form through frequent interactions among co-located entrepreneurs and firm employees (Owen-Smith and Powell, 2004; Inkpen and Tsang, 2005). Narratives about the social interactions in clusters suggest that they are spontaneous and occur through chance encounters at local bars or Sunday soccer events (Saxenian, 1994;

Malmberg, 2003). Although this may be true of social relations in general, using network analysis, recent works show that knowledge networks in regional clusters are not randomly structured. Rather they have informal hierarchical structures (Giuliani, 2007; Ter Wal, 2010), likely driven by several underlying micro-level forces. While an understanding of the dynamics of networks is an indication of cluster aims and success, little is known about these micro-level forces.

The second limitation is that research so far is focused almost entirely on advanced economies and high tech 'hot spots' (Pouder and St John, 1996); it is only recently that management and organization scholars have begun to focus on regional clusters in emerging/developing economies (Mesquita and Lazzarini, 2008; McDermott et al., 2009; Perez-Aleman, 2010).[1] Also, a disproportionate number of network studies of regional clusters relate to the US biotech industry (Owen-Smith and Powell, 2004; Casper, 2007; Gittleman, 2007; Tallman and Phene, 2007; Whittington et al., 2009) and other high tech advanced country clusters (Ter Wal, 2010; Bell and Zaheer, 2007; Fleming and Frenken, 2007), and use co-patenting to track knowledge flows and social networks (e.g. Singh, 2005; Gittleman, 2007). However, as emerging economies are becoming dominant players in international competition, studies focused on such contexts are crucial for informing theory and management practice (Hoskisson et al., 2000). The conditions normally taken for granted in studies focusing on advanced countries may not hold for emerging/developing economies (Perez-Aleman, 2010). One important difference is that in developing and emerging economies the presence of firms with accumulated skills and capabilities cannot be assumed: firms that have caught up with the technological frontier to become world-class producers (Khanna and Palepu, 2000; Bhattacharya and Michael, 2008) may co-exist with firms where intra-firm accumulation of capabilities does not occur at all (Bell and Pavitt, 1993; Cimoli et al., 2009; Perez-Aleman, 2010). In these contexts, the process of learning and accumulation of technological capabilities is often hampered by macroeconomic instability, lack of business confidence, weak state capacity and poor institutions (Arza, 2005), which leave many firms at the margins of domestic and global competition.

This paper addresses these limitations by studying the evolution of the inter-organizational knowledge network of a wine cluster in an emerging country, Chile. In this context, knowledge networks are built on the seeking and provision of informal advice by the enologists and agronomists employed by the wineries in a cluster. They capture the knowledge flows among the wine producing firms that compete in the market. The hypothesis is that the evolution of a knowledge network is determined by the co-occurrence of three sets of micro-level effects. *Cohesion* effects, which assume that knowledge network growth is characterized by greater cohesion and network closure among firms – a view that coincides with many cluster narratives but which has not been tested empirically. *Status* effects, which suggest that more prominent firms in terms of their links, tend to reinforce this prominence through the formation of more ties over time, especially relevant in the resource-poor and uncertain contexts that frequently characterize developing/emerging countries. The third effect is the *capability* effect, which refers to how heterogeneity in firm-level knowledge bases influences the formation of new knowledge ties. These three effects are driven by different and sometimes contrasting underlying motivations, which nevertheless can co-exist in clusters. The impact of each of these effects on network dynamics may differ. Cohesion is bound to lead to more egalitarian and dense networks, while status and capability effects are likely to promote fragmentation and hierarchy within the network structure (Gould, 2002; Giuliani, 2007). This paper seeks to answer the following questions: What are the micro-level effects leading to the evolution of knowledge networks in regional clusters? How do micro-level effects shape the macro-level structural characteristics of networks?

We analyze a wine cluster, Valle de Colchagua (CV), in one of the most thriving wine areas in Chile (Schachner, 2002, 2005). Data were collected through face-to-face interviews conducted by the author. The survey was based on the same structured questionnaire, administered to the population of wineries (32 firms) in the cluster in 2002 and again in 2006 - a period of cluster expansion. Social network analysis (Wasserman and Faust, 1994) is employed to conduct static comparisons between knowledge networks over time, and *cohesion*, *status* and *capability* effects are tested using a class of stochastic actor-based models of network dynamics, based on Stocnet SIENA as a tool for analysis (Snijders, 2001, 2005). The empirical results show that there are two main micro-level effects guiding the network dynamics in CV. *Cohesion* effects promote greater density in the cluster knowledge network by reinforcing the core of innovating firms. *Capability* effects keep firms with weak knowledge bases on the periphery of the knowledge network. This paper provides a new interpretation of cluster network dynamics, in which networks do not simply become more egalitarian or denser over time due to endogenous network dynamics, often seen as a natural consequence of co-location. We show that the knowledge network supports an informal hierarchy which is based on the existence of significant differences in the knowledge bases in the cluster, with some firms being particularly resource-poor and displaying poor socialization dynamics. This result is novel and has important implications for the cluster competitiveness and network studies literatures and the burgeoning literature on corporate behaviour in emerging economies (see Section 6 Discussion).

The paper is organized as follows. Section 2 outlines the Chilean wine industry context and describes the CV cluster and its inter-organizational knowledge network. The research hypotheses are presented in Section 3, and Section 4 describes the methodology for data collections and analysis. Section 5 presents the empirical results, which are discussed in Section 6 which concludes the paper.

2. Research Context: a Chilean wine cluster

2.1 Export-led growth in Chile and the importance of natural resource-based industries

Chile is a small country but is one of the most thriving economies in Latin America. Based on exports from natural-resource based industries, e.g. mining, agroindustry and fishing, since 1990 Chile has enjoyed sustained economic growth, a doubling of per capita income and a reduction in absolute poverty, although income inequality remains high (Perez-Aleman, 2005; Infante and Sunke, 2009).

One sector that has achieved stunning export value growth is the wine industry. Wine production has a long tradition dating back to the Spanish-Mexican Jesuits who came to Latin America in the 19th century (Del Pozo, 1998); however, it is only since 1990 that the industry has boomed in line with increased international demand for wine (Giuliani et al., 2010). The spectacular performance of Chile's wine industry is evidenced in the export statistics: in 1994 Chile accounted for only 1.73 percent of total wine exports, by 2004 its share was 4.6 percent (a 266% increase). In the same period, instead, traditional wine producing countries, such as Italy, Spain, Portugal and France, lost market share and experienced a reduction of export values as a percentage of world wine exports (on average -17%). In 2007 Chile was ranked 4th for wine export volume (1,157,808 tonnes) (after the traditional wine producing countries of Italy, France and Spain) and wine export value ($US2,414,119,000) (after France, Italy and Australia).

2.2 The CV cluster

Export-oriented growth in the O'Higgins' region where the CV is located, has been impressive. This region is about 200 km south of Santiago, the capital of Chile. Between 1990 and 2005, agricultural and agro-industrial activities, such as wine production, saw the value of their exports rise from US$ 3m to US$161m (Ramirez and Silva Lira, 2008). The

CV has been responsible for much of this increase and is one of the most thriving and successful wine areas in the country (Schachner, 2002, 2005). The cluster is densely populated by wine producers and grape growers; other firms in the upstream and downstream wine production value chain are located outside the cluster territory, close to Santiago and other major urban areas, or abroad. As a result, the vertical division of labour within the cluster is fairly shallow. The CV cluster also includes a business association, aimed primarily at promoting the wines and marketing them locally, but with no specific mandate to foster innovation or facilitate dissemination of technical knowledge.

At the time of the first survey (2002), the CV wine industry was beginning to taste success following ten years of steadily increasing investment.[2] New modern wineries had been established and there was a general feeling that CV was set to become one of the leading wine areas in Chile. Despite the problems inherent in rural Chile (especially inadequate infrastructure), private investors, mostly powerful Chilean families, were making major efforts, sometimes jointly with public institutions (e.g. CORFO)[3] to renovate and modernize the industry and catch up to the technological frontier. Already in 2002, some Colchagua wineries were as modern as the wineries in advanced countries, and many firms were using advanced technologies, employing skilled knowledge workers (oenologists and agronomists) and undertaking substantial experimentation in their vineyards and cellars. This was reflected in the wines which increasingly were being cited and rated in international specialized wine journals, such as *Wine Spectator*, *Decanter*, *Wine Enthusiast*, etc.[4] Nevertheless, a considerable number of the firms in the cluster were technological laggards in 2002.

By 2006 the situation had changed dramatically. The most visible change was the improvement to the local infrastructure including new paved roads and a training institute for local students to specialize in wine production, and plans for a research laboratory and a technology transfer office allied to the University of Talca. The cluster was promoting a set of marketing initiatives ranging from strengthening the wine route to setting up new ventures connected to the flourishing local economy (promotion of local artisans, fairs, restaurants, etc.) These changes were paralleled by a continuous commitment of the wineries to match international wine quality standards. In 2005 Colchagua was awarded "Wine Region of the Year" by *Wine Enthusiast*, and in 2007, *Wine Spectator's* Top 100 wines included two Colchaguan wines.

This case is a particularly appropriate context for this study. First, it is a successful case from the developing world, where some firms have managed to compete at the international frontier and achieve quality standards that challenge leading wine producers such as France, Italy and the US. Second, it is dynamic. The impressive improvements in production quantity and quality are based on the efforts of firms to learn and innovate, and are giving rise to a dynamic inter-organizational knowledge network at the local level. Third, in the period considered in this study the cluster was experiencing a growth phase, which was neither disturbed by external macroeconomic or market shocks nor subjected to policy interventions to alter the structure of the local inter-organizational network. It is thus an ideal setting for exploring the emergence of spontaneous micro-level mechanisms of network dynamics.

2.3 The inter-organizational knowledge network in CV

Local knowledge networks typically are built through the interactions of technical professionals, in this case the agronomists and enologists and other technicians employed by the wineries in the cluster, who seek advice on technical problems that cannot be solved in house – which is consistent with other industry accounts (e.g. von Hippel, 1987; Saxenian, 1994). For example, advice may be sought about how to treat a pest infestation or how to deal with high acidity levels during wine fermentation. These networks become established when the wineries are committed to improving their products via incremental innovation based on the solutions to technical problems, reached through the advice of professionals working in other wineries.

Inter-organizational networks have some important properties. They are built initially through the informal interactions among individuals (agronomists, enologists, technicians), who are the gatekeepers of the firm's technical knowledge and how apply the knowledge acquired from other firms to their organizational routines. This is consistent with the industrial cluster literature, which describes linkages among firms as often poorly formalized through contracts and based mainly on workers' and managers' personal connections. Inkpen and Tsang (2005, p. 153) argue that " connectivity between network members in an industrial district is usually established through informal interpersonal relations". Such networks operate in a similar way to communities of practice in other contexts (Brown and Duguid, 1991; Wenger and Snyder, 2000). Agronomists and enologists transfer and receive technical advice from professionals in rival firms in the cluster such that the network operates as a community in which knowledge exchange is not controlled by firm owners who might be worried about knowledge leakage (Powell and Grodal, 2005). Also, the interviews conducted during the pilot and main fieldwork demonstrate that inter-organizational knowledge networks are not explicit and formalized endeavors to increase and promote 'cluster-brand' reputation. In other words, the formation of knowledge linkages is not the result of a planned and organized cooperation strategy, but is an informal and spontaneous networking process.

3. Theory and Hypotheses

Network studies tend to suggest that the evolution of the macro structural characteristics of a network is driven by concurrent forces operating at the micro level (Owen-Smith and Powell, 2004; Powell at al. 2005). Some are endogenously induced by the existing network – e.g. past relationships influence future ones (Walker et al., 1997; Gulati and Gargiulo, 1999) and firms occupying similar structural positions in a network are likely to be connected in the future (Rosenkopf and Padula, 2008) - while others are exogenously-driven, which means that they are related to the heterogeneity in the internal and individual characteristics of the actors in the network. For instance, in a study on inter-firm alliances, similarity in firms' technological and market specializations was found to influence future collaborations (Gulati and Gargiulo, 1999), while diversity, rather than similarity has been shown to drive repeated formation of ties in the US biotech industry (Powell et al., 2005). Therefore, to investigate the dynamics of a network, it is important to explore the mix of exogenous and endogenous network effects that drive its evolution and how these effects shape its macro-structural characteristics (Di Maggio, 1992).

In the context of industrial clusters one of the endogenous network effects is *cohesion*. This is described in numerous cluster narratives that report inter-organizational ties as being characterized by reciprocity, and highlight that geographical proximity enables close knit social relations among the firms in the cluster (Aydalot and Keeble, 1988; Pyke et al., 1990; Saxenian, 1994). No empirical test of whether cohesion influences the network dynamics in regional clusters has been conducted. However, it would be plausible that, in the absence of any other effect, cohesion would produce increasingly egalitarian, dense and all-encompassing networks that discourage the formation of hierarchical structures (Granovetter, 1973). Other studies in the field of economic geography have sparked thinking about a different view of the network dynamics in clusters. It has been shown that even successful 'hot spot' regions may be spaces where informal relations are fragmented and structured very hierarchically (e.g. Ter Wal, 2010). This points to the need to study the other effects that may underpin network dynamics alongside cohesion. We think that two types of effects are important. One is *status*, which network scholars consider to be a powerful source of asymmetric relationships and hierarchical network structures (Gould, 2002). The second relates to differences in firms' characteristics in terms of abilities to orchestrate and contribute to the local knowledge network. This paper considers differences in firms' *capabilities* and *knowledge bases* as pivotal in shaping network relations (Cohen and Levinthal, 1990).

In order to test the simultaneous roles of *cohesion*, *status* and *capability* effects in network dynamics, an inter-disciplinary conceptual framework is proposed, drawing on (a) organizational sociology and network theories (e.g. Granovetter, 1973, 1985; Powell et al., 2005); (b) economic geography (e.g. Amin and Thrift, 1994; Aydalot and Keeble, 1988; Storper, 1997); and (c) evolutionary theories of firm's learning and innovation (e.g. Nelson and Winter, 1982; Dosi, 1988; Bell and Pavitt, 1993; Dosi and Nelson, 2010).

3.1 Cohesion effects

Cohesion occurs when firms are connected by stable, closed and dense social structures. I consider that cohesion within a network can be increased by reciprocity, and by transitive closure. In the context of this paper, reciprocity emerges when a firm that has been the recipient of technical advice from another firm, decides to return (reciprocate) the favour. While reciprocity is common in human behavior (Gouldner, 1960), its motivations and drivers have been studied as mechanisms promoting the formation of new ties in inter-corporate networks (Lincoln et al., 1992; Fehr and Gachter, 2000), with reciprocal ties found often to occur in the case of rival firms (von Hippel, 1987). If the firm decides to behave opportunistically, it will not reciprocate the advice received. Opportunistic behaviour occurs when the firm does not want to dissipate its proprietary knowledge by transferring pieces of knowledge that may increase the competitiveness of other firms.

In the context of industry clusters, instances of opportunistic behavior are usually minimal (Amin and Thrift, 1994). Smith-Doerr and Powell (2005, p. 20) argue that, in industrial districts, "repetitive contracting, embedded in local social relationships, encourages reciprocity. Monitoring is facilitated by social ties and constant contact." Likewise, Grabher

(1994, p. 181) describes East German regional industry in the 1970s as characterized by the emergence of informal networks, which "provided diffuse infrastructure for barter governed by the principle of reciprocity." In such contexts, reciprocity is guided by two underlying motivations. The first is that reciprocal relationships are beneficial because they stabilize relationships and increase levels of trust between the parties, which in turn minimizes transaction costs. The second is that, within a spatially bound area, instances of opportunistic behavior are quickly broadcast. A bad reputation in relation to opportunism will sever existing ties and discourage formation of new ties with other firms. Hence, over time, reciprocation should become a safe strategy for firms keen to take advantage of the pool of local knowledge. This leads to the following hypothesis:

> **Hypothesis 1 (HP 1)** In regional clusters, the search for reciprocity leads to the formation of new knowledge linkages among firms.

Transitive closure also encourages network growth and increases cohesiveness. It occurs when a new link is formed between two actors that are already connected to a common third actor. Underpinning transitive closure is what is known in social psychology as "balance theory" (Heider, 1958), which suggests that an individual establishes a new linkage with a third one on the basis of whether, the individuals she/he is already connected to, have positive feelings about (and are themselves connected to) this third person. Basically, the idea is that an individual perceives a sort of psychological pressure from her/his direct contacts (e.g. friends) and is induced to choose new contacts in a way that preserves some consistency and harmony (or balance) within the social group that she/he is part of (Granovetter, 1973).

Studies on regional clusters generally do not refer to the concept of transitive closure, but include many stories that are persuasive about the existence and importance of network closure and are indicative of the tendency for firms to become embedded in dense networks

(Becattini et al., 1991). These ideas are not too dissimilar to the tradition in studies of economic geography of "untraded interdependencies" (Storper, 1997), "innovative milieux" (Aydalot and Keeble, 1988; Camagni, 1991) and "collective learning" (Capello and Faggian, 2005). For instance, Inkpen and Tsang, (2005, p. 153; emphasis added) consider that "a characteristics of an industrial district is *dense*, non hierarchical networks of firms located within the district, with some of them forming cliques." Likewise, Scott (1988, p. 31; emphasis added) defines industrial localities as "agglomerations [of producers] that coalesce out of the *dense* networks of transactional interrelations that form as the social division of labour deepens and as particular groups of producers are brought into intense and many-sided interaction with one another."

One of the main reasons for firms to form triads, is that they represent social spaces where relationships can be monitored easily, which guards against opportunistic behavior and is likely to give rise to intense exchanges of valuable, tacit and fine-grained knowledge (Uzzi, 1997). In other words, they are spaces where the local "mysteries of trade become no mysteries" (Marshall, 1920, p. 271) and where knowledge is used and improved. In regional clusters the formation of triads may be facilitated by geographical proximity which provides previously unconnected professionals with numerous opportunities to get to know each other, e.g. at local social events, and to "close" the triplet. Additionally, when firms are operating in close proximity, their professional staff can seek out relationships that reduce antagonisms and promote a better working environment, thus seeking 'balanced' relationships. This leads to the following hypothesis:

Hypothesis 2 (HP 2): In regional clusters, the search for transitive closure leads to the formation of new knowledge linkages among firms.

3.2 Status effects

While cohesion effects strengthen the connections among firms already in direct or indirect contact, status acts as a signal for firms with no prior contacts in the network and little knowledge about where to seek advice. Status is defined here as the perceived quality of an actor; prominent status signals reputation within the community (Podolny, 1993). Ibarra and Andrews (1993) and Lazega et al. (2010) among others, suggest that, under conditions of uncertainty and ambiguity, the search of advice is socially-derived. This means that the most centrally positioned actors in a network are those that most rapidly gain reputation because of the information about them that diffuses through their many direct linkages. The most prominent actors are frequently cited, which contributes to their aura. In addition to reducing uncertainty, selection of a prominent actor may be preferred to selection based on quality judgments because the latter "are costly to make" (Gould, 2002, p. 1149).[5] Key to the status effect is whether the existence of a prominent firm shapes the evolution of the knowledge network in a regional cluster over time. There are two ways that this may occur: preferential attachment (de Solla Price, 1976; Barabasi and Albert, 1999) and assortativity (Newman, 2002).

Preferential attachment is based on the idea that firms guided by status when searching for technical advice, will target prominent firms. This behavior is common among new entrants with no prior knowledge of the other firms in their competitive environment (e.g. Rosenkopf and Padula, 2008), but can be associated also with incumbent firms in a regional cluster. In particular, while it is true that "proximity makes information about local competitors more available because managers are better able to scan the activities of local competitors compared to the activities of outside competitors"(Pouder and St. John, 1996, p. 1996), the extent to which this information is easily accessible to *all* cluster firms is debatable. Firms that are particularly resource-poor may be able neither to collect reliable information about the quality of the other firms, nor to judge their value. In a survival or rural cluster in a developing country, for example, many firms' observational scope may be limited by the routine of day-by-day activities and time, and the flexibility required to search and accumulate valid information about other firms may be limited. In other cases, the number of cluster firms may mean that scanning the quality of all potential sources of advice is too time-consuming. For these reasons, status may be a valid and time-saving criterion to decide which firms to approach for advice. This leads to the following hypothesis:

> **Hypothesis 3 (HP 3)** In regional clusters, firms with a prominent status are likely to form more linkages over time.

The second status effect is assortativity, which refers to the preference of an actor to attach itself to others with similar status (Newman, 2002). This adds to the preferential attachment effect, and it proposes that cluster firms with high status may achieve satisfaction from interacting with firms with similarly good reputations. Also, while preferential attachment is likely to be asymmetrical - the prominent firm transfers some knowledge to lower status firms, but not vice versa (Gould, 2002) – assortativity is more balanced way because both parties have something to gain. The connection is established both to enable sharing of resources and also to create a local self-reinforcing elite of reputable firms. These coalitions of firms may constitute a valid strategy for pooling reputation and building or strengthening regional identity (Romanelli and Khessina, 2005), especially in clusters that have not achieved complete international visibility. This leads to hypothesis 4:

> **Hypothesis 4 (HP 4)** In regional clusters, firms tend to form new linkages with firms with a similar status.

3.3 Capability effects

Endogenous network effects – cohesion and status – are important but on their own do not acknowledge the significant organizational variation among co-localized firms (Baum and Mezias, 1992). It is proposed that the formation of new knowledge linkages may be influenced by both endogenous network effects and the fact that firms differ in one important dimension, their *knowledge base*, which is critical for the establishment of knowledge linkages (Cohen and Levinthal, 1990). Firms vary widely in their patterns of learning and knowledge creation. Their knowledge bases are built through a process of cumulative learning, which is inherently imperfect, complex and path-dependent (Nelson and Winter, 1982; Arthur, 1988; Dosi, 1988), characteristics that result in persistent differences among firms. These differences are likely to be even more profound in emerging/developing country firms, many of which are behind the technology frontier (Perez-Aleman, 2010). Also, a tradition of studies on firm-level learning in developing countries suggests that firms in such context may remain technological laggards over decades, as the accumulation of capabilities through training and knowledge generation efforts require dedication and commitment and does not occur overnight (Bell and Pavitt, 1993).

Studies of regional clusters focusing on advanced countries tend to ignore this aspect. Studies that do take account of differences among firms' knowledge bases usually focus on qualitative differences, essentially the presence/absence of technological overlaps in areas of specialization (Cantner and Graf, 2006; Tallman and Phene, 2007). The approach proposed here considers the *quantitative* differences in firms' knowledge bases: some are *more advanced* than others in terms of the quality and experience of their professional technical workers, and some are more intensively involved in knowledge-creating activities. This paper suggests two ways in which heterogeneity in the strength of knowledge bases influences the formation of new knowledge linkages: through *similarity* and *threshold* effects.

The similarity effect implies that firms predominantly prefer to establish knowledge linkages with other firms at the same level of technical or knowledge advancement. This is because both parties can take advantage of a pool of knowledge that is similarly sophisticated, which will facilitate interactive learning. If knowledge bases are too dissimilar, linkages will be less likely. When knowledge bases are very different, firms will have different problems and will be less likely to be able to help each other. Thus similarity in knowledge bases influences the formation of future knowledge ties.

> **Hypothesis 5 (HP 5):** In regional clusters, firms with similar strengths in terms of their knowledge bases are more likely to form new knowledge linkages than firms with dissimilar knowledge bases.

The *threshold* effect is a mechanism that is seldom considered in explanations of the formation or not of new ties. It refers to new linkages that are formed only if the parties have some valuable characteristics that are over a certain threshold level (e.g. status, power, wealth, skills, etc.). Actors with below-the-threshold characteristics are less likely to form linkages. Masuda and Konno (2006) consider the threshold effect to be a determinant of the formation of elite groups, where hierarchy decides about new entrants based on their characteristics. We would emphasize that in given contexts, individuals with characteristics below a certain given threshold do not establish linkages with those whose characteristics position them above the threshold *or* those with similar sub-threshold characteristics. An example is homeless people, who have similarly fragile and precarious conditions, but seldom interact with each other (Rokach, 2004; Hersberger, 2007). It applies also to people with psychological disorders or low levels of education (McPherson et al., 2006).

One reason why the *threshold* effect is generally not considered in studies of network dynamics in regional clusters is because most focus on resource-rich actors (e.g. inventors, innovative firms) as their unit of analysis. However, there is significant anecdotal evidence of lack of socialization among resource-poor entrepreneurs in other areas of research. Altenburg and Meyer-Stamer (1999) report cases of survival clusters in Latin America, often located in the shanty towns of large capital cities or in isolated rural areas. These clusters are described as inhabited by people who are self-employed or employed in informal workshops, and who suffer from severe resource-constraints: "most of these persons do not have substantial savings at their disposal…they typically do not master modern management techniques and lack the ability to organize and continuously improve production in a systematic way" (Altenburg and Meyer-Stamer, 1999, p. 1696). In such environments, they note, "the culture of imitation makes entrepreneurs reluctant to share any kind of information; opportunistic or even predatory behaviour may pay off, because many firm owners perceive their business as a survival activity to sustain them until a better opportunity arises." (Altenburg and Meyer-Stamer, 1999, p. 1697). This view is reflected in other studies, which show that when firms have very few resources their socialization patterns diminish significantly (Visser, 1999).

In this paper, we suggest that there is a *threshold* effect based on firms' knowledge base which conditions the formation of new knowledge linkages. It is argued that firms with weak knowledge bases are unlikely to increase their knowledge linkages over time. To support this, it is suggested that firms with very weak knowledge bases have modest knowledge resources to draw on and are unlikely therefore to be sought out for their knowledge by other cluster firms (Giuliani and Bell, 2005). It is suggested also that these firms may lack the internal capacity to absorb the stock of knowledge available in other cluster firms (Cohen and Levinthal, 1990). This leads to the last hypothesis:

> **Hypothesis 6 (HP 6):** In regional clusters, the poorer the firm's knowledge base the smaller the probability that the firm will form new knowledge linkages over time.

4. Method

4.1 Data

This study is based on firm level data collected in the CV cluster at two points in time: 2002 and 2006. Prior to the main fieldwork, exploratory interviews were conducted to obtain in depth knowledge on the wine industry in Chile and its contextual and historical background. Some 50 interviews were conducted with agronomists and oenologists from several Chilean firms (other than those in Valle de Colchagua) and other experts, including several representatives of the main Chilean business associations and consortia. The questionnaire was tested in pilot interviews with agronomists and oenologists also working in firms outside the CV cluster. The main fieldwork interviews followed the same procedure. All interviews in both periods were based on an almost identical structured questionnaire, were face-to-face and conducted in August-September in both years.[6] The wineries survey did not include suppliers or clients – mainly because with the exception of grape growers these actors are located outside the cluster boundaries. Interviewees were skilled workers (i.e. oenologists, agronomists) in charge of the production process at firm level; interviews lasted 90 minutes on average. The surveys in both years covered the whole *population* (32 firms) of fine wine producers in the cluster.

Table 1 shows how the characteristics of firms have changed over the four years – reflecting cluster development. Their increased size is particularly striking: in 2006 nearly half (48%) employed more than 100 people, compared to only 6 per cent in 2002. In 2006 the proportion of firms with fewer than 20 employees was less than 10%, the average size of firms having doubled from 55 to 110 in the period. The number of firms established since 2000 has increased from six to ten: two exited before 2006, and six new entrants joined the cluster. This pattern reflects a broader pattern of entry and exit in the cluster, with six firms exiting and six entering.[7] The proportion of foreign owned firms increased by about one-third by 2006. This is not a direct result of entry and exit: all new entrants were domestic firms that established new businesses, and one of the six exiting firms was foreign owned. The increased foreign ownership is the result of acquisitions of incumbent businesses by foreign owned firms and the involvement of one domestic incumbent in a joint venture partnership with a foreign owned firm.

[Table 1 about here]

In addition to the general firm-level variables presented in Table 1, the questionnaire was designed to collect other information relevant to this study: (i) about within-cluster inter-firm knowledge linkages; (ii) firms' knowledge bases. Relational data for (i) were collected using the roster recall method (Wasserman and Faust, 1994): firms were given a list (roster) of the other wine producing firms in the cluster and asked about innovation-related knowledge transfer. *Q1* and *Q2* (reported below) were directed to the agronomists and enologists employed by the wineries and focus on problem solving and technical assistance and efforts to improve or change the firm's economic activity. Knowledge transfer is usually in the form of a response to a query about a problem:

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 [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].

Since the data were collected in two waves (2002 and 2006), the relational data are expressed in two matrices composed of 32 rows and 32 columns, corresponding to the number of firms in the cluster in each year. The cells in the matrix show 1 for the existence of a tie between firm *i* in the row to firm *j* in the column and 0 otherwise.[8] The matrix is asymmetric given that, as with any advice network, the transfer of knowledge from firm *i* to firm *j* may not be bi-directional.

A composite indicator with three dimensions was used to measure firms' knowledge bases: (a) human resources' formal training; (b) human resources' experience in the field; and (c) firm experimentation intensity (see below). While (a) and (b) refer to the human resources at the time of interview (2002 and 2006), (c) takes account of experimentation up to two years prior to the interviews (the pilot fieldwork showed that a 2 year time span was sufficient to indicate the intensity of firms' experimentation activity). None of the variables is influenced by local network ties, thus can be considered to capture characteristics that are exogenous to the knowledge network. The variables were defined as follows:

(a) Human resources' formal training: represents the cognitive backgrounds of the firm's knowledge/skilled workers measured by level of education. In line with previous work on the returns to education, it is assumed that the higher the education degree, the greater will be the contribution to the firm's knowledge and innovation activity. Each knowledge/skilled worker is weighted according to the education degree awarded:

$$Human\ Resource = 0.8^{*}\ Degree + 0.05^{*}\ Master + 0.15^{*}\ Doctorate$$

A 0.8 weighting is applied for the number of graduate employees and highly specialized workers in the firm. This weight is increased by 0.05 times for number of employees with a masters degree and 0.15 for number of employees with a PhD degree.[9] Only degrees and higher level specialization in technical and scientific fields related to wine production (i.e. agronomics, chemistry, etc.) are considered.

(b) Human resources' experience: is the months of work experience of the qualified human resources. Number of months is indicative of the accumulation of knowledge via 'learning by doing'. The variable is the result of a weighted mean of months of work of each knowledge skilled worker in Chile and abroad:

Months of Experience in the Sector= 0.4 n° months (national)+ 0.6* n° months (international)*

A higher weight is given to time abroad because the diversity of the professional environment might stimulate active learning behaviour and a steeper learning curve. Again, only learning experience related to wine industry activity is considered.

(c) Experimentation intensity is a proxy for knowledge creation efforts. In the wine industry context indicators such as R&D expenditure and number of patents are neither available nor meaningful. Therefore this concept is operationalized on the basis of the specificities of the context. Based on lengthy consultation with industry experts, it was decided to capture experimentation intensity in terms of the number of production phases in which experimentation was carried out, i.e. experimentation related to the introduction of different clones or varieties to the vineyard *terroir*, management of irrigation and vine training systems, fermentation techniques and enzyme and yeast analysis, and analysis of the ageing period. Experimentation intensity was measured on a 0-4 scale (firms with no in-house experimentation score 0).

Although these variables measure different aspects of the knowledge base, they are highly correlated - especially *Human Resource* and *Months of Experience in the Sector* (> 0.7) – making construction of a composite indicator for firm's knowledge base (*KB*) appropriate. The composite indicator was extracted using Principal Component Analysis. A single factor was extracted representing more than 70% of data variation, and referred to as firm *KB*.[10] This measure ranges from -1.278 to 2.050 in 2002 and from -1.873 to 1.152 in 2006.[11]

4.2 Analysis

The analysis is undertaken in two steps. First, a static comparative analysis of network structure in the two periods considered (2002 and 2006), based on the set of network structure indicators presented in Table 2(a). Second, the research hypotheses are tested on the basis of the stochastic actor-based model developed in Snijders (2001, 2005) and implemented using SIENA (Snijders et al., 2007). The model assumes that the changing network can be interpreted as the outcome of a Markov process and that actors control their outgoing ties. The idea is that when actor *i* decides to make a change to her/his outgoing tie variables (x_{i1}, ….., x_{ig}), this will depend on a series of effects related to with actor's network position and her/his individual characteristics and those of the other actors in the network. An actor selects the change that provides the greatest increase in the objective function, which represents the preference distribution of the actor over the set x of all possible networks. This function depends on unknown parameters that are estimated from the data. The objective function is represented as a weighted sum depending on a parameter $\beta = (\beta_{1, \ldots,} \beta_L)$ and $f_i(\beta, x) = \sum \beta_k s_{ik}(x)$.

x is the network at time *t*, and the functions $s_{ik}(x)$ represent different types of effects that may influence network change over time and which are included in the model in line with the conceptual framework and research hypotheses. This paper considers a total of six effects: reciprocity and transitive closure (*cohesion* effects); out-degree popularity and assortativity (*status* effects); similarity effect and ego-activity (*capability* effects). A summary of the effects and guidance on how to interpret the results is presented in Table 2(b). SIENA estimates the model based on a method of moment, implemented as a continuous-time Markov chain Monte Carlo simulation. To approximate the solution of the moment equation the stochastic approximation proceeds in three steps. First, a covariance matrix is calculated to estimate the algorithm. Second, a choice process simulation based on starting values, compares the resulting simulated network with the observed second period of the network and adjusts the values to reduce the differences between the simulated and observed data. Third, simulations are used to determine the frequency distribution of the errors in predictions, which are used to calculate the standard errors for the final parameter values. The simulations were repeated several hundreds of times.

[Table 2 here]

5. Results

5.1. Network characteristics and changes over time

This section presents the results of the static comparative analysis of the knowledge networks in CV, in 2002 and 2006. Table 3 presents the key structural indicators and shows that the overall density of the network has increased greatly, from 0.0938 in 2002 to 0.2301 in 2006. This large increase in the total number of links in the network could be interpreted as increased inclusion of cluster firms in the knowledge network, reflecting a more egalitarian diffusion of knowledge among cluster firms. The comparative values of other cohesiveness indicators reflect this: average distance has decreased by some 40 percent (from 2.155 in 2002 to 1.756), and fragmentation has halved (from 0.442 to 0.238), indicating a significant decrease in the number of disconnected firms in the network. Increased cohesiveness is reflected also in mutual ties, which account for 75 percent of total ties in the 2006 network, nearly double the 2002 value (43%). Also, the share of isolated firms on total cluster firms slightly diminished from 19 percent in 2002 to 13 percent in 2006.

Despite the increased density and reciprocation, the distribution of knowledge linkages has not varied over time. The GINI coefficient of degree centrality, which measures the degree of concentration of knowledge ties in the network, is the same (0.45) over the period, suggesting that the network's structural features have not varied significantly over time.

[Table 3 here]

To explore this further, the structural forms of the cluster network in 2006 and 2002 are depicted in Figures 1 and 2 and compared in Table 4, which shows that in 2002 the network has a core-periphery structure[12] which is even more marked in 2006 (final fit, indicating the extent to which the network matches a pure core-periphery structure, increased from 0.433 in 2002 to 0.861 in 2006). Also, the density of core-to-core relations increased (from 0.341 in 2002 to 0.864 in 2006), while peripheral firms persist in being poorly connected to the core and especially to other peripheral firms (periphery-to-periphery density is 0.032 in 2002 and 0.045 in 2006). Thus, the structural features that were present in 2002 –cohesive core and a loose periphery - persist over time. More important, the data show that over time 60 percent of the firms that were peripheral in 2002 were still peripheral in 2006 and 30 per cent had exited the cluster and the industry. Only 10 percent of peripheral firms had joined the core by 2006. Similarly, the majority of 2002 core firms maintained that position through time. This explains why, despite increased network density, network linkages continued to be distributed in the same uneven way. In summary, over time network density has increased but the overall core-periphery structure and linkage distribution have not changed.

[Figures 1-2]

[Table 4]

5.2 Micro-level mechanisms of network dynamics

What are the micro-level mechanisms responsible for the (lack of) network dynamism observed in CV? This section reports the empirical results of the actor-oriented network model estimations based on the SIENA analysis and tests the research hypotheses. Table 5 reports the estimation results. The rate parameter and density effects are reported by default in this type of estimation. The rate parameter is positive and significant in all models indicating a significant change in the formation of new ties; the negative and significant coefficient of density indicates that firms tend to differentiate among firms when establishing knowledge linkages in the cluster (Snijders et al., 2007).

Model 1 tests Hypotheses 1 and 2 about the importance of *reciprocity* and *transitive closure* for the formation of new ties. As expected, reciprocity is a very strong and significant driver of the formation of new knowledge ties (β=2.832 and s.e. 0.5184), which provides strong support for Hypothesis 1. The network shows a tendency for transitive closure, although this effect is not as strong as the reciprocity effect, evidenced by the smaller coefficient size (β=0.3994 and s.e. 0.0780).[13] This result supports Hypothesis 2 that there is an endogenous *cohesion* effect which increases the overall density of the knowledge network.

Model 2 includes the *status* effects of preferential attachment and assortativity, neither of which are significant.[14] In Model 2 the β coefficient for *out-degree popularity* effect, which measures the existence of a preferential attachment phenomenon, is positive but small and not significant (β=0.0577 and s.e. 0.0564), which does not support Hypothesis 3. Likewise, similar status (assortativity) does not increase the likelihood that two actors will form a new knowledge tie. Rather, the estimation results suggest the opposite (β = - 0.0201 and s.e. is 0.0846); however the lack of significance does not enable further hypothesizing about this result. Hypothesis 4 is not supported.

Model 3 tests the role of *capability* effects in the formation of new knowledge ties. Because parsimony is very important in this type of model, *status* effects, which were not significant in Model 2, were dropped. The model includes a control for firm size (number of employees) and for firm nationality, because the the formation of new ties may be also influenced by these firm-level characteristics. A knowledge base *similarity* effect is used to test Hypothesis 5. Contrary to expectations, the coefficient is positive but barely significant (β=0.7503 and s.e. 0.4046), which does not provide full support to Hypothesis 5. This result is commented on later in the paper. The β coefficient for the *threshold* effect is negative and significant (β=-0.4225 and s.e. 0.1642), suggesting that firms with less solid knowledge bases are less likely over time to form new knowledge linkages, which supports Hypothesis 6. Also, the β coefficient for threshold effects is almost as double the value observed for transitivity, which indicates that the latter exerts a comparatively weaker effect on the formation of new knowledge ties.

Table 6 shows that in both 2002 and 2006, isolated or peripheral firms in the knowledge network, tend to have lower level knowledge bases on average than other firms in the cluster. This is evidence that firms with particularly weak knowledge bases are only poorly connected to the cluster knowledge network and, more importantly, that firms with weak knowledge bases do not form linkages with similar alters, demonstrated by the low density of intra-periphery ties (see Table 4). This result explains the weak support for Hypothesis 5: while it is plausible that similarity matters when firms' knowledge bases are above a certain threshold, firms with similarly-weak knowledge bases do not establish linkages with each other, which reduces the power of *similarity* effect as an explanatory variable.

[table 5]

[table 6]

6. Discussion

The results of the empirical analysis are interesting for several reasons. The structural configuration of the knowledge network does not change significantly over time. Despite increased density and increased number of ties, the core-periphery structure present in 2002 is consolidated in 2006, with peripheral firms persistence over time. This result is not surprising *per se* in the context of previous studies on other contexts than regional clusters, which show that networks are stable (e.g. Walker et al., 1997; Uzzi et al., 2002). However, most of the existing work is on the social structures that characterize mature systems, which "typically display a set of stable, self-reproducing positions occupied by actors with similar network profiles"(Gulati and Gargiulo, 1999, p. 1450). The context here is one of a dynamically growing cluster, trying to catch up and compete in the international market, where one would expect much more variation, and especially towards a more egalitarian network structure. As Pyke et al. (1990: p. 1) state clusters can be places "exhibiting a remarkable resilience and *even* growth." In our case, we observe persistence of an informal hierarchy between the core and peripheral firms.

To explore how this result has been achieved we need to look at the results of the SIENA analysis about the micro-level drivers of new tie formation. First it shows that *cohesion* effects are important because *reciprocity* and *transitive closure* are key drivers of the formation of many new knowledge ties. This evidence is consistent with narratives of regional clusters that describe them as places where networks are dense and cohesive, and with much of the organizational sociology literature on inter-organizational networks (Pyke et al., 1990; Saxenian, 1994; Inkpen and Tsang, 2005). Qualitative insights from the survey interviews confirm that reciprocity is beneficial in stabilizing relationships over time, which helps to make interactions more fluid and spontaneous. In terms of the benefits from transitive closure, an enologist suggested in interview that "*three is an ideal number to solve a problem: you have three brains to count on, who interact and share different expertises, and you reach a solution quickly. Discussions with more than three people are also fruitful but they are often lengthy and less effective.*" Interviewees also confirmed that geographic proximity acts as a significant trigger for triadic closure: "*there are many occasions within clusters in which professionals with whom I have a tie meet each other and start interacting.*"

However, this does not fully explain network dynamics: it is only part of the story and possibly the least interesting part. Cohesion effects can be assumed to be responsible for the increased density of linkages *among* core firms. However, while cohesion effects reinforce the core, the *threshold* effect keeps firms with weak knowledge bases at the periphery of the cluster knowledge network. In CV, firms characterized by weak knowledge bases are untouched by local socialization dynamics and not affected by the strength of the cohesion effects in the cluster. This can be interpreted by referring to Cohen and Levinthal's (1990) idea of absorptive capacity. Cohen and Levinthal contend that the capacity of firms to form linkages with external actors depends on their knowledge bases, since the ability of a firm to recognize the value of new, external information, to assimilate it, and apply it for commercial ends, requires prior accumulated knowledge (Bell and Pavitt, 1993). Hence, firms with very weak knowledge bases are unlikely to be able to scan and use external knowledge and because their knowledge resources are modest, they will be unlikely to be sought out to contribute knowledge to other cluster firms.

Studies focusing on advanced economies often overlook the role played by the weakest firms in maintaining the structural properties of networks unaltered over time. This is because the unit of analysis in many such studies is resource-rich firms or individuals (e.g. inventors or innovative firms). Including these actors in studies of network dynamics provides an alternative and new interpretation of hierarchical structure formation, which in the literature is associated predominantly with status and prominence (e.g. Gould, 2002).

In the present study, hierarchy is associated with the heterogeneity of firm knowledge bases rather than to status differences. In light of this result, we need to examine the possible reasons for the lack of status effect and its implications for network dynamics. One explanation might be that, within regional clusters, uncertainty about firm quality is mitigated by firms operating in the same environment which makes it more likely that information can be gleaned first hand and there is no need to rely on status when deciding about links (Pouder and St John, 1996). However, the interviewees had a different interpretation. One described it as "*not all of us have access to such information not because it is secret, but because to be able to understand the real quality of something or someone you need to have some accumulated experience on that particular quality aspect.*" On this basis, there might be firms that will be bound to rely on status rather than effective qualities, especially in resource-poor contexts. Although counterintuitive, this would explain the finding of lack of status effects: firms that are better able to access and scan information firsthand, by definition, do not rely on status while those firms that might rely on status to orient themselves, i.e. firms with fewer resources and weak knowledge bases, do not form linkages, as shown by the *threshold* effect.

As a result of concurrent cohesion and threshold effects, the knowledge network in CV is structured spontaneously in a way that is functional to its success. In particular, while no leading hub firms emerge, there is a core of elite firms, which account for about a third of the cluster, which becomes consolidated. This network structure is effective for two important reasons. First, it is not vulnerable to the behavior of a few leading firms, which means that the network is not likely to be disrupted by, for instance, the decision of a hub firm to relocate or exit the industry; second, its core-periphery structure enables the circulation of high quality, tacit and fine-grained knowledge among the densely connected core firms, whose potential to upgrade knowledge is higher, and whose strong knowledge bases facilitate knowledge transfer. At the same time, the persistence of a core-periphery structure minimizes the risk that transferred knowledge becomes 'downgraded' by firms with weaker knowledge bases, as such firms are persistently relegated to marginal network positions. This spontaneous emergence and consolidation of a network structure is interesting. Also interesting is our observation for CV that firms achieve a macro-structural knowledge network configuration, where benefits are collective and go beyond those that might be achieved from the micro-level interactive choices of individual firms.

This research contributes to literature in three ways. First, it contributes to the growing field of studies of geography, networks, and performance (Bell, 2005; Gittleman, 2007; Tallman and Phene, 2007; Bell and Zaheer, 2007; Mesquita and Lazzarini, 2008; Whittington et al., 2009). While there is a certain consensus that local network embeddedness plays a role in firm-level innovation success and competitiveness, little is known about how network embeddedness is created or enforced over time. This paper represents a step forward by showing the importance of cohesion effects, but also that heterogeneity of firms' characteristics may have a greater influence even than endogenous network effects, in shaping the evolution of a network over time. There are two lessons from this study. First, the geographic proximity of firms in a regional cluster may act as a significant push for increased network cohesion over time, but only if firms have internal resources above a certain minimum threshold. Second, resource poor firms have no internal push for or interest in forging new linkages and therefore do not contribute to local network dynamics despite their geographical proximity. In clusters where most firms are resource-poor it is unlikely that geographic or social endogenous forces will trigger more inclusive participation in knowledge-rich networks. This explains why resource-poor regions never become the leaders in international competition despite policy initiatives designed to strengthen local linkages.[15] These results should inform scholars interested in cluster competitiveness in developing/emerging countries and those interested in backward regions in the advanced world.

The paper also has implications for the literature on corporate behavior in emerging countries (Hoskisson et al., 2000; Cuervo-Cazurra and Dau, 2009), which assumes that emerging/developing economies suffer from severe market failures and institutional weaknesses. In this context, firms that want to enter the international competition need to cultivate and join different types of inter-organizational networks e.g. business groups or interpersonal networks, such as the *guanxi* in China. These networks provide access to resources, reduce information asymmetries among firms, enable higher bargaining power vis a vis other market counterparts, increase lobby power towards governments, and allow firms to upgrade their capabilities (Guillén, 2000; Peng and Lou, 2000; Khanna and Palepu, 2000; Khanna and Rivkin, 2001; Hitt et al., 2000; Chang et al., 2006; Stark and Vedres, 2006; Acquaah, 2007; Mesquita and Lazzarini, 2008). They act as safety nets against uncertainty and unfavorable business climates. This paper makes a contribution by showing that firms may be incapable of becoming members of the relevant networks. Despite the growing power of emerging economies in the current global competitive scenario, there are huge parts of these economies where backwardness and isolation prevail. The extent to which isolated or marginal firms will be able to connect to valuable networks and close the gap with the most powerful and successful firms in their own countries will affect the competitiveness of these emerging countries with the advanced economies. This study shows that even firms that could become easily part of the local network, thanks to the presence of cohesion effects, face a divide that exists and persists over time. Understanding how this divide can be reduced is a challenge for research on the future competitiveness of emerging and developing economies.

Finally, this paper contributes to the literature on inter-organizational network dynamics. One of the challenges in this area is to disentangle the relative impact of endogenous and exogenous micro-level behavior on macro-level network dynamics. While there is a significant body of research focusing on endogenous network effects (e.g. Walker et al., 1997; Rosenkopf and Padula, 2008), little attention has been paid to the individual actors and their characteristics (Stuart, 1998; Powell et al., 2005; Fleming and Frenken, 2007). Owen-Smith and Powell (2004, p. 5) point out that in network research "limited attention has been paid thus far on how important non-structural features – such as the characteristics of the organizations that represent nodes in the network … - alter the character of information flows." This paper adds to this line of research. Also, while most existing research is anchored in secondary data and formal linkages (e.g. alliances, co-patenting activity, formal R&D arrangements), this paper offers some insights on the dynamics of informal networks.

The analysis in this paper has some important limitations, which provide opportunities for further research but also suggest some caution in how the findings are interpreted. First, it is based on a single case study, which limits the extent to which the results can be generalized. However, the research design in this study can be replicated and it would be interesting to see similar research on other sectors in the developing world. Second, it focuses on only one type of local network: the knowledge network. This choice has been based on exploratory research involving hundreds interviews with industry experts and representatives worldwide, which suggested that an inter-organizational knowledge network based on technical advice seeking/giving would be the most meaningful in terms of problem solving and innovative outputs. However, other studies could look at other types of networks. Third, it focuses on local ties but does not take account of external linkages. Firms in the CV cluster have connections with national and international actors; however, this study does not explore whether firms' structural equivalence within a network that includes external actors, influences the ties within the cluster, which would be an interesting direction for future research. Fourth, the data on the existence of relationships are binary, and do not include information on their value or strength. The choice to use binary data was because they are the only type of data SIENA handles and because dichotomizing for higher values of the valued relationships (i.e. higher than or equal to 2) would have resulted in a significant loss of ties. Given the fact that this is a small case study this seemed not appropriate. Fifth, the paper does not account for the impact of entry/exit patterns, the interest being focused on incumbent firms. However, the firms that exited the industry in 2006 were those with the weakest knowledge bases in 2002, showing that exit is more likely than network inclusion. Lastly, this research tracks only a snapshot of the cluster growth period (2002-2006); studies on network dynamics that rely on secondary data typically are able to cover longer periods. However, it should be acknowledged that primary longitudinal relational data are extremely rare.

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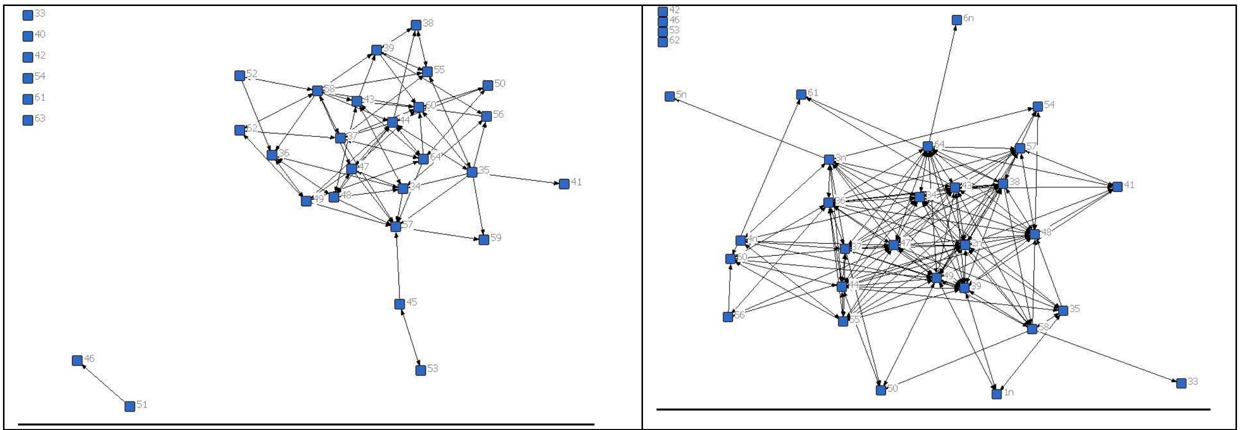
Figures



1 (a) The knowledge network in 2002 | **1 (b) The knowledge network in 2006**

Tables

Table 1 Firm characteristics in the two survey years

Characteristics of firms		**2002** (N= 32)	**Entry/Exit** 2002 - 2006	**2006** (N= 32)
(a) Size (number of employees)				
Small (1-19)	(%)	28		9
Medium (20-99)	(%)	66		43
Large (≥100)	(%)	6		48
Average Number of Employees per firm	(number)	55.5		110.5
(b) Year of establishment				
Up to 1970s	(number)	6	-1	5
During the 1980s	(number)	8	-1	7
During the 1990s	(number)	12	-2	10
During the 2000s	(number)	6	-2 + 6	10
(c) Firm entry and exit: 2002 - 2006				
Exit – Number of firms	(number)		6 (5 domestic)	
Entry - Number of firms	(number)		6 (All domestic)	
(c) Ownership				
Domestic	(%)	81		66
Foreign	(%)	19		34

Table 2 Summary of key measures for the analysis of the knowledge network

2 (a)	Measures for comparative static analysis of networks
Density	Network density (*ND*) is defined as the proportion of possible linkages present in a graph. *ND* is calculated as the ratio of the number of linkages present, *L*, to its theoretical maximum, $g(g-1)/2$, where *g* is the number of nodes in the network: $ND = L / [g(g-1)/2]$. *ND* value range from a minimum of 0 to a maximum of 1.
Average distance (among reachable pairs)	The average of geodesic distances between nodes in the network. The distance is the length of a geodesic between them, which is measured as the shortest path.
Fragmentation	Proportion of nodes that cannot reach each other.
Mutual linkages on total linkages (%)	Percentage of reciprocated ties on total ties in the network.
Share of Isolates	Percentage of firms with no connections to other firms in the cluster.
GINI Coefficient for firms' degree centrality	Distribution of knowledge linkages measured by the GINI coefficient applied to degree centrality (*DC*). *DC* is number of knowledge linkages established by a firm with other firms in the cluster, irrespective of the direction of the linkage.

2(b)	Measure and effects for SIENA Analysis
Cohesion effects:	
Reciprocity	A positive and significant β coefficient means that reciprocation is the means chosen by an actor to maximize its objective function through the formation of new knowledge ties.
Transitive triplets	A positive and significant β coefficient means that new ties are formed by closing triads of firms where two connections existed in the previous period.
Status effects:	
Preferential attachment	This is tested through the out-degree popularity effect. A positive and significant β coefficient effect reflects the tendencies for actors with high out-degrees (i.e. outgoing knowledge ties) to attract extra incoming ties in the subsequent period.
Assortativity	This is tested through the out-out assortativity effect. This effect tests for the existence of actor preference to form new ties with actors with similar out-going ties. A positive and significant β coefficient means that firms that provide more technical advice to others at time 1 tend to form linkage among themselves in the subsequent period.
Capability effects:	
Similarity	A positive and significant β coefficient means that ties tend to occur more often between firms with similar values in their knowledge base (*KB*).
Threshold	To carry out this test, the variable *KB* was transformed into *Inv-KBi*= (Max *KB* –*KBi*). This inverts the vector of *KB* values so that firms with the weakest knowledge bases have the highest scores in this indicator and vice versa. The effect applied in SIENA is *Inv-KB* actor activity. A significant and negative β coefficient suggests that the weaker the firm's knowledge base the lower the probability that the firm will form new knowledge ties, indicating the presence of a threshold effect.

Table 3 Changes in the knowledge network: descriptive comparative data

Indicators:	2002	2006
Density	0.0938	0.2301
Average distance (among reachable pairs)	2.155	1.756
Fragmentation	0.442	0.238
Mutual linkages on total linkages (%)	43%	75%
Isolates on total firms (%)	19%	13%
GINI Coefficient for firms' degree centrality	0.45	0.45

Table 4 Core-periphery structures in 2002 and 2006

2002	The Density of Linkages* (Knowledge transfer from row to column)		Final Fit
	Core	Periphery	
Core *(n_c=12)*	0.341	0.096	**0.433**
Periphery *(n_P=20)*	0.054	0.032	
2006	**Core**	**Periphery**	
Core *(n_c=12)*	0.864	0.230	**0.861**
Periphery *(n_P=20)*	0.206	0.045	

Note (*): Densities are calculated on dichotomous data..

Table 5 Results of SIENA Analysis

	Model 1 Coeff (s.e.)	Model 2 Coeff (s.e.)	Model 3 Coeff (s.e.)
Rate Parameter	11.7037 (1.8892)	10.8179 (1.7317)	14,0709 (2,2233)
Density	-2.4199 (0.3060)	-2.5463 (0.5995)	-2,3681 (0,2584)
Reciprocity	**2.8132** **(0.5184)**	**2.8322** **(0.6136)**	**2,7097** **(0,4479)**
Transitive triplets	**0.3994** **(0.0780)**	**0.3981** **(0.1116)**	**0,2937** **(0,0832)**
Preferential Attachment		0.0577 (0.0564)	
Assortativity		-0.0201 (0.0846)	
Knowledge base similarity			0,7513 (0,4199)
Threshold			**-0,4156** **(0,1782)**
Size of ego (control)			0.0003 (0.0010)
Nationality of ego (control)			-0,0820 (0,3198)

Note: Results of stochastic approximation. Estimated parameter based on 987 iterations. The convergence of the models was good in all cases (t-ratios were all inferior to 0.10 for all coefficients in all models) and no severe problems of multicollinearity were encountered.

Table 6 Exploring the threshold-effect of knowledge base in 2002 and 2006

	Average KB 2002	Average KB 2006
(a) Isolated firms		
Isolates	**-0.88**	**-1.22**
Rest of the firms	0.58	0.31
ANOVA test (*p*-value)	0.000	0.001
(b) Peripheral firms		
Periphery	**-0.45**	**-0.40**
Core	0.58	0.59
ANOVA test (*p*-value)	0.000	0.000

Endnotes

[1] There is an extensive literature on industrial clusters of developing countries (one of the pioneering studies being Schmitz, 1995). However, these works do not specifically focus on knowledge networks and look at how clusters and inter-firm cooperation impact on economic development.

[2] The available data indicate that, within the cluster, the number of hectares of vines planted for wine production almost tripled from 1997 to 2002 (www.sag.gob.cl).

[3] CORFO is Corporacion de Fomento, a Chilean government institution that promotes industry development.

[4] E.g., the number of times Colchagua's wines have been cited annually by *Wine Spectator* increased 10-fold in the period 1994-2002.

[5] This does not mean that prominence is established in a vacuum and it is totally independent on the real and observable qualities of an actor. However, as suggested by Gould (2002: 1146) "socially influenced judgments amplify underlying differences, so that actors who objectively rank above the mean on some abstract quality dimension are overvalued while those ranking below the mean are undervalued."

[6] The 2006 questionnaire included some slight modifications which did not affect the key variables used in this paper.

[7] Note that entry and exit of 6 firms does not mean that the exiting firms were taken over by the new entrants. It is coincidental that over the period studied there was perfect turnover, thus the overall population of the firms in the cluster did not change, resulting in 32 operating firms in both observed periods.

[8] Only dichotomous data are used for the purpose of this paper. SIENA analysis does not process valued data.

[9] The weights are defined *ad hoc*. The indicator was calculated using other weights without significant differences for the analysis.

[10] Factor loadings and uniqueness are available upon request.

[11] To cross-check the validity of this measure, the questionnaire has a section on qualitative descriptions of the type of production methods and experimentation activities carried out by each firm (objectives, length, methods of analysis, etc.) This information was used to check for a correspondence between the quantitative KB indicator and the knowledge base of the CV firms as reflected by more qualitative insights. Two experts were consulted (an academic and a consultant) to give an external assessment of the strength of the knowledge base of each firm in the cluster on the basis of the qualitative information collected. Cross-checks were generally confirmatory of the usefulness of the KB indicator to capture the strength of firms' knowledge bases.

[12] Core/Periphery Models are based on the notion of a two-class partition of nodes, namely, a cohesive sub-graph (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 (Borgatti and Everett, 1999).

[13] Alternative measures of transitivity and network closure were used to test this hypothesis (transitive ties; balance effect; three-cycle effects), all gave significant results but the transitive triplet effect was strongest.

[14] The model was also tested considering the two measures separately.

[15] Based on the author's direct knowledge of cluster policies and cluster policy evaluations.