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WHAT DRIVES INNOVATIVE OUTPUT IN EMERGING CLUSTERS?
Evidence from the wine industry

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Abstract

This paper explores the drivers of innovative output of firms that belong to emerging clusters, defined as those clusters that are not as “vibrant” or leading as e.g. Silicon Valley, but yet strive to emerge in the international competition. Using evidence of two wine clusters in Italy and Chile, this paper finds that firms’ internal knowledge bases and their external openness are more significant than intra-cluster network embeddedness in explaining innovation. In particular, the paper tests for two competing structural positions within the intra-cluster knowledge network – network closure and structural holes – and finds that network closure affects innovation but with diminishing returns. However, this variable looses significance when accounting for external openness. Implications for managers of emerging clusters are noted.

Key words: Industrial clusters, innovative output, firm knowledge base, network closure, structural holes, external openness, wine.

JEL Classification: M0, O32, O33, Z13

1. INTRODUCTION

Industrial clusters are often considered to enhance the innovative performance of their firms, and they have for this reason attracted the attention of management and organization scholars in recent years (e.g. Porter, 1990; Pouder and St John, 1996; Bell, 2005; Tallman et al., 2005; Romanelli and Khessina, 2005) – following a long tradition of studies in the field (Marshall, 1920). Industrial clusters are defined as geographic agglomerations of firms specialized in one or more connected industries and examples of successful clusters include Silicon Valley in California (Saxenian, 1994), or the Cambridge Region in the UK. Due to their success, clusters are often referred to as "hot spots" (Pouder and St John, 1996, p. 1192) and have become an important feature of national competitive landscapes, with a vital role in the ability of firms to innovate (Porter, 1998). Beyond thriving clusters as the ones mentioned above, the world is replete with clusters that are not considered as "hot spots", but that make an effort to compete on an international scale. These types of clusters have mostly attracted the attention of regional economists, geographers and development scholars (e.g. Schmitz and Rabellotti, 1999; Giarratana et al., 2004; Morosini, 2004; McDermott et al., 2007), while they have seldom been at the centre of management studies. However, the increased competitive pressure exerted by newly emerging countries and regions (Bhattacharya and Michael 2008) as well as the crisis of some historically successful clusters (see e.g. in Italy), calls for a more in-depth understanding of how firms, operating in clusters that are not as "vibrant" as e.g. Silicon Valley, manage to be innovative. This paper intends to contribute to this issue.

In particular, the paper questions one property of industrial clusters that is generally regarded as being responsible for the innovative output of firms: local network embeddedness (Granovetter, 1985). As a consequence of their geographic proximity, cluster firms are considered to be strongly embedded into local networks (e.g. Watts et al., 2006). Employees and entrepreneurs are frequently considered to be nested within densely connected networks and to be involved in a number of informal social linkages at local level, which are in turn believed to foster trustful and cooperative behaviours among competing firms (Porter, 1998). Also, embeddedness is often considered to be a *pervasive* property of clusters – one that permits knowledge to be diffused more evenly across cluster firms and raises the innovative output of firms accordingly (Maskell and Malmberg, 2002).[1] This paper argues that, in clusters that are not thriving "hot spots", local network embeddedness might not be such a key driver of innovation, while other factors play a more significant role. In order to delve into the factors that influence innovation in cluster firms, three questions are explored.

The first is related to the role of the individual firm: how much of the success and innovation of a cluster can be ascribed to firms' internal capabilities and strategies and how much should be attributed to meso-level factors that are external to the firm and specific to the cluster (see e.g. Maskell, 2001) is an open question. This paper does not explicitly test this comparative question. Instead, it considers a specific micro-level dimension, the knowledge base of firms, which in this context is the quality of a firm's knowledge workers and their experimentation efforts (Nelson and Winter, 1982; March, 1991), and it claims that there exists a positive relationship between this dimension and the innovative output of cluster firms.

The second question is related to the limitations of current research into the measurement of key concepts in cluster theory, particularly the concept of "embeddedness", which is often associated with the innovative potential of cluster firms. This has seldom been studied in an empirically rigorous way (Johannisson and Ramirez-Pasillas, 2002; Hess, 2004; on a similar issue, see also: Markusen, 2003). Given the fact that recent studies have shown that not all firms are as embedded or positioned as equally within a cluster knowledge network (Giuliani, 2007), we need to understand what type of embeddedness is more beneficial to innovation in cluster firms. This paper makes a significant contribution in this direction, as it looks at the relationship between two types of embeddedness in local networks – i.e. a firm's position as bridge between structural holes, and its degree of ego-centred network closure – and their innovative output. Firms that bridge structural holes, on the one hand, link

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[1] Partly because of firms' geographic proximity, partly because co-located entrepreneurs tend to operate in a common socio-institutional *milieu*, industrial clusters are often conceived as places where "the flow of industry-related information and knowledge is generally more abundant, to the advantage of all firms involved" (Maskell and Malmberg, 2002; p. 433)

firms that are not directly connected to each other, a structural position that is considered to enhance innovation because it allows a certain amount of knowledge "diversity" to be accessed, raising firms' creativity and innovation (Burt, 1992; 2001). However, this paper claims that, in industrial clusters, firms that bridge structural holes are not in a particularly desirable position. This is because the degree of knowledge diversity that can be achieved at the intra-cluster knowledge level is limited due to the very narrow scope of the knowledge sources within the cluster, all represented by firms operating within the same territory. On the other hand, therefore, we claim that the degree of ego-network closure (Coleman, 1988), a condition in which the firm's direct contacts are densely connected to each other, enhances innovation as it may facilitate access to "deep" knowledge (Laursen and Salter, 2006), that is, fine-grained knowledge, oriented to the solution of specific technical problems. This is based on the fact that network closure is considered to breed trustful and stable relations, to reduce opportunism and to favour the transfer of reliable intra-firm knowledge, which could not otherwise be accessed (Granovetter, 1985; Coleman, 1988; Uzzi, 1997).

The third open question in cluster research is about the significance of extra-cluster networking for innovation. Scholars have emphasized the importance of accessing knowledge outside cluster boundaries (Bell and Albu, 1999, Bathelt, 2005), because this can widen the scope of knowledge diversity a firm can access. However, very little empirical work has been done on the relative importance of extra-cluster linkages with respect to local embeddedness. This paper argues that external openness, defined here as the variety of extra-cluster sources of knowledge a firm relies upon for its innovative activities, is a way through which firms can access a wide scope of ideas and knowledge. This enriches the knowledge base of a firm by adding distinctive new variations and consequently improves their innovative output (Katila and Ahuja, 2002; Laursen and Salter, 2006).

This paper explores these issues in two wine clusters, one in Italy and one in Chile. The wine industry was chosen for three main reasons. The first and more important reason is the availability of data, as this is one of the few studies to have gathered complete networks for industrial clusters; the second is related to the technological change and evolution of the industry since the mid 1980s; and the third was based on the simple organizational forms of wine producers.

The paper is organized as follows: Section 2 presents the theoretical framework and outlines the research hypotheses. Section 2.1 examines the first open question, namely how the knowledge base of cluster firms influences their innovative output. Section 2.2 discusses the relationship between firms' embeddedness in local knowledge networks and innovative output, and Section 2.3 explores the third question about the significance of extra-cluster networking for innovation. Section 3 describes the empirical setting of this study and the method of data collection and analysis. Section 4 presents the empirical results and Section 5 discusses the results and concludes.

2. THEORY AND HYPOTHESES

2.1 Cluster firms need internal capabilities to innovate

Traditional work on clusters has emphasized that there is something special at the local level that renders firms operating within the boundaries of geographical clusters more innovative than dispersed firms. At least part of this literature is based on the Marshallian "industrial atmosphere" idea (Marshall, 1919) and refers to the fact that there is some "knowledge in the air" (Marshall, 1920) that pervades the entire population of cluster firms and enhances their innovativeness.

More recently, however, scholars have pointed out that simply being "exposed" to knowledge flowing "in the air" does not necessarily enhance firms' innovativeness and some internal effort is required for firms to absorb external knowledge and to exploit it commercially (Cohen and Levinthal, 1990; Giuliani and Bell, 2005). This means that firms need to have invested in substantial accumulation of knowledge (Nelson and Winter, 1982; Bell and Pavitt, 1993), which enables the building up of a knowledge base, defined as "the set of information inputs, knowledge and capabilities that inventors draw on when looking for innovative solutions" (Dosi, 1988, p. 1126). As innovation scholars suggest, the process of accumulating knowledge is inherently imperfect, complex and path dependent, resulting in persistent heterogeneity of firms (Nelson and Winter, 1982; Grant, 1996).

An important first source of such a heterogeneity is related to the use that firms make of knowledge workers. Knowledge workers are defined as creative, bright employees, who possess the skills to do knowledge work and to solve complex technical problems (Subramaniam and Youndt, 2005). As such, they are responsible for sparking innovation and growth within an organization. For this reason, firms with the highest quality knowledge workers tend to be the fastest-growing and most profitable. In the context of the wine industry, knowledge workers – the agronomists and oenologists – are important for the diffusion and implementation of new methods of production and for fostering innovation. Their scientific understanding of viticulture and oenology has made them a key resource in the recent technological modernization of the wine industry.

The second source of heterogeneity in firms' knowledge bases is tied to the different intensity with which knowledge workers carry out exploration and research and development (R&D) within the firm. Internal exploration is a prerequisite for achieving a technological lead, which enables higher returns (Wernerfelt, 1984). Internal exploration also deepens the uniqueness of the resources deployed to compete in international markets through differentiated and innovative products (Nelson and Winter, 1982). In the wine industry, internal experimentation to develop innovative wine blends that will satisfy emerging new tastes is quite critical.

The skills of knowledge workers and the propensity of a firm to experiment are both components of a firm's knowledge base and, for the reasons discussed above, it is plausible that its knowledge base positively influences the firm's innovative output. The first hypothesis therefore can be formulated as follows:

> ***Hypothesis 1*** The strength of a cluster firm's knowledge base is positively associated with its innovative output.

So far I have considered firms' internal capabilities, in the sections that follow the relationships with other firms at the intra- and extra-cluster levels will be examined.

2.2 Local embeddedness and cluster firms' innovative output

2.2.1 Embeddedness: what it means for cluster scholars and network researchers

Scholars writing about industrial clusters have incorporated the concept of embeddedness in their theories for a long time. Inspired by the neo-Marshallian accounts of Italian industrial districts as socio-economic phenomena (Pyke et al., 1990), as well as by Granovetter's (1985) argument about the importance of social links in influencing economic action, over the years cluster scholars have demonstrated an interest in whether and how social embeddedness favours the diffusion of knowledge among firms, and their innovative process (e.g. Porter, 1998). By embeddedness, scholars typically refer to the overwhelming presence of social linkages within the economic space of industrial clusters. These linkages enable employees and entrepreneurs to maintain a number of market and social contacts, which often foster trustful and cooperative behaviours – a view that is in line with Storper's (1997) idea of "untraded interdependencies", with the concept of "institutional thickness" proposed by Amin and Thrift (1995) and with the Alfred Marshall's (1919) pioneering idea of "industrial atmosphere".

Based on a wealth of qualitative and/or ethnographic empirical work (e.g. Saxenian, 1994), cluster scholars have contributed to the idea that the more a firm is "embedded" into an industrial cluster, the higher will be its innovative or economic performance (Pyke et al., 1990; Porter, 1998; Tallman et al, 2004; Boschma, 2005). Indeed, embeddedness is often considered to be one of the strengths of industrial clusters, rendering it a successful form of industrial organization. As Watts et al. (2006, p. 187), suggest, for example, "local embeddedness is one of the key theoretical concepts underpinning the view that clusters of economic activity can provide a solid basis for local and regional economic growth…".

In spite of wide acceptance of this view in the cluster literature, the number of studies that have tried to operationalize the concept, and have attempted to measure its effects and the implications it may have for cluster theory, are still limited (Johannisson and Ramirez-Pasillas, 2002; Hess, 2004). Conversely, network researchers have paved the way to rigorous definition and analysis of the concept of embeddedness, although their studies have not specifically focused on industrial clusters. Several of the contributions from this literature are particularly notable for the purposes of this paper.

A key contribution from network research is Granovetter's (1992) distinction between *relational* and *structural* embeddedness. Relational embeddedness refers to the quality and strength of inter-firm, dyadic, direct relations. These are important drivers of economic action because, as Gulati (1998) puts it "actors who are strongly tied to each other are likely to develop a shared understanding of the utility of certain behaviour as a result of discussing opinions in strong, socialising relations, which in turn influence their actions" (p. 296). Structural embeddedness, on the other hand, has to do with the "structure of the overall network of relations" of an actor (Granovetter, 1992, p. 33). In this paper, we define structural embeddedness in terms of "the position a firm occupies in the overall structure of a network" (Gulati, 1998, p. 296), and it is observed on the basis of the degree to which a firm's direct contacts (i.e. alters) are (are not) connected to each other.

As already mentioned in the Introduction, over the past decade or so, two opposing views have sparked debate in network research about which structural position better enhances a firm's innovative performance – having a "close" ego-centred network (Coleman, 1988) or bridging "structural holes" (Burt, 1992). However, these initially competing views have progressively converged and recent research shows that there need not to be primacy of either the one or the other, and also suggests that the different ways in which firms are structurally embedded in networks can lead to different results based on certain contingencies – e.g. type of industry (Rowley et al., 2000) or type of innovation process of interest to the firm (e.g. incremental vs radical, exploitative vs explorative, etc.) (Ahuja, 2000; Rowley et al., 2000). Quite surprisingly, this issue has not yet been explored in any analytical depth in the context of industrial clusters, although qualitative insights on these aspects have been often offered by cluster scholars.

2.2.2 *Ego-centred closure in the intra-cluster knowledge network leads to higher innovative output through the access of "deep" knowledge*

There can be a set of advantages associated with the closure of a firm's ego-centred knowledge network.[2] First, this type of structural position is a precondition for the emergence of *trustful relations* - an important governance mechanism, since it reduces both uncertainty and information asymmetries in the interactions between two firms (Coleman, 1988). Second, this type of structure allows the exchange of more *fine-grained information*, which is more proprietary and tacit than the information exchanged in more open networks; and third, it entails effective joint *problem-solving* arrangements that speed up responses to the market (Uzzi, 1997).

Hence, cluster firms may have an interest in being embedded in close ego-centred networks of knowledge because this structural position permits them to find several reliable and valid solutions to their specific technical problems. In this sense, the underlying claim of this literature is that the higher the degree of closure of a firm's ego-centred knowledge network, the more innovative will be the firm, as it helps firms to achieve deep understanding of a specific innovation (Zaheer and Bell, 2005). Thus, close networks facilitate better access to "deep" knowledge, defined here as highly contextual and tacit knowledge (Uzzi, 1997) – a unique and distinguishable asset of firms within clusters.

However, whereas a certain degree of network closure can be beneficial for innovation, too much of it can be detrimental (Boschma, 2005). As Gargiulo and Benassi (2000) caution, when firms are too closely embedded in a network, the risk is that they get "trapped in their own net" (p. 183). In fact, close ego-networks may breed relational inertia and obligations for reciprocity. This in turn may have the effect of cementing relationships into a stable network structure, even when these relationships are no longer beneficial and result in firms relying only on knowledge from their trusted alters, rather than experimenting with other sources, generating a risk of negative technological lock-in (Grabher, 1993).

[2] A knowledge network is defined here as a network that links cluster firms through the transfer of innovation-related knowledge, aiming at the solution of complex technical problems.

Hence the relationship between embeddedness and innovative output is likely to be positive, but with decreasing returns, as indicated in the following hypothesis:

> ***Hypothesis 2*** *The relationship between the degree of closure of a firm's ego-centred knowledge network and its innovative output is non monotonic taking an inverted U-shape.*

In addition, this paper tries to incorporate the strength of ties into structural embeddedness. It considers the degree of firms' ego-centred closure in networks characterized by strong ties only. Strong ties are regarded as being particularly persistent, of high quality and of value to the parties engaged in the interaction. The paper argues that, if the ties within the ego-centred knowledge network are all strong, closure is likely to have a more pronounced effect on a firm's innovative output than when ego-centred network closure involving both weak and strong ties is considered – as in Hypothesis 2 above. This means that, on the one hand, when a firm's ego-centred knowledge network is characterized by close and strong ties, this allows a better access to "deep" knowledge, and nurtures their innovative process via such strong linkages. On the other hand, however, such a position may lure firms into a local "trap", to use Gargiulo and Benassi's (2000) expression, since strong ties are particularly difficult to disrupt. Thus, we can formulate the following hypothesis.

> ***Hypothesis*** **3** *When ties in a firm's ego-centred network are all strong ties, the effect of the degree of closure of the network is non-monotonic and inverted u-shaped.*

In this section we have focused on key elements of the intra-cluster embeddedness (i.e. ego-network closure), but we have not yet considered the issue of 'structural holes'– 'holes' being defined by the absence of cross-linkages among firms that are connected to a focal firm.

2.2.3 Firms bridging structural holes in industrial clusters are less likely to innovate

Innovation scholars also believe that, to be creative, firms require a certain amount of informational "diversity" (Laursen and Salter, 2006), as they need to combine ideas coming from different sources during their experimentation and R&D activities. Drawing on Burt's structural holes theory (1992; 2001), network scholars have suggested that such diversity is achieved when a firm's direct contacts are not densely connected to each other, and thus there is a "hole" in the knowledge network structure. Structural holes theory thus suggests that firms acting as brokers in a knowledge network, thereby connecting otherwise disconnected firms, have access to potentially more diverse knowledge, which enhances their creativity. Recent studies that support this view have shown that firms bridging structural holes are more innovative than other firms (McEvily and Zaheer, 1999; Zaheer and Bell, 2005).

However, in this paper we claim that being a bridge of structural holes is not a particularly desirable position within industrial clusters. Because the variety of knowledge sources is likely to be limited in scope within the same industrial cluster – all represented by firms operating within the same territory – we consider that bridging structural holes may not facilitate the access of truly innovative ideas and, in addition, that in this position firms will fail to take advantage of the presence of a wealth of highly contextual "deep" knowledge, which is instead accessed more easily through ego-centred network closure – as suggested by Hypotheses 2 and 3. For this reason, we would expect firms that bridge structural holes in clusters to have lower innovative than that of firms not so positioned, which leads to the following hypothesis:

> ***Hypothesis 4*** *The relationship between the degree to which a firm bridges structural holes in the intra-cluster knowledge network and its innovative output is negative.*

In this section, we have focused on different types of structural positions in the intra-cluster knowledge network. What follows extends beyond the local context, to a larger system, which considers knowledge linkages with actors outside the cluster boundaries.

2.3 External openness and cluster firms innovative output

Cluster scholars have increasingly emphasized the importance of accessing knowledge outside the cluster boundaries to avoid problems of negative lock in and to rejuvenate the local knowledge over time. Probably, extra-cluster linkages are the means through which diversity in knowledge is achieved – hence structural holes might be better bridged at the global, rather than at the local level. Cluster firms can access knowledge from a vast array of extra-cluster actors, spanning suppliers and clients, to university laboratories and consultants. The variety of extra-cluster sources of knowledge a firm relies upon for its innovative activities is defined here as "external openness". In spite of the interest demonstrated by cluster scholars in external openness, very little empirical work has been done to explore the relationship between extra-cluster linkages and innovation (see e.g. Bathelt, 2005).

Innovation scholars have suggested that there is a positive relationship between the external openness of firms – conceived as the diversity of knowledge sources that firms can access – and their innovative output, although they have not specifically directed their attention to industrial clusters (e.g. Shan et al., 1994; Laursen and Salter, 2006). Katila and Ahuja (2002), for example, find that external openness – which they define as "search with high scope" **-** enriches the knowledge base of a firm by adding distinctive new variations. This in turn provides the firm with sufficient choice to solve problems. In other words, since there is a limit to the number of new ideas that can be generated using the same set of knowledge sources, an increase in scope improves the possibility of finding new combinations, thus enhancing product innovation.

The existence of a positive relationship between external openness and firm innovation has been documented in other studies (see e.g. Laursen and Salter, 2006). However, these authors also find that "over-searching" by firms will incur negative consequences for their innovative output. One such is that too many sources of knowledge may imply too many ideas for the firm to manage and choose from. Also, too many ideas, means that few are awarded the level of attention or effort required to implement them. It is considered that external openness has diminishing returns to innovation. In line with these conceptual arguments, we hypothesize that:

__Hypothesis 5__ The relationship between the external openness of a cluster firm and its innovative output is non monotonic taking an inverted U-shape.

3 METHODOLOGY

3.1 The choice of the industry

This empirical study is based on two wine clusters for three main reasons. The first and more important one is the availability of data on complete networks for these clusters. Complete networks are very difficult to obtain for industrial clusters, both because of the high number of firms that commonly populate such contexts and also for the low response rate that characterizes this type of research. The wine industry resulted to be a favourable setting because it was possible to find clusters populated by a workable number of firms (see Section 3.2 for a description of the two clusters studied here) and also for the good disposition of interviewees towards relational questions. This has led to the development of a unique relational dataset, through which we have explored network concepts in greater detail than achieved by previous cluster studies (see also McDermott et al., 2007).

Second, the wine industry makes an interesting case for analyzing the processes of knowledge transfer and innovation. In the past fifteen years or so, this industry has undergone a significant advances in production processes, involving worldwide improvement in the practices of wine production. This has changed the way in which wine producers operate, such that the wine industry is no longer a traditional industry where tacit knowledge predominates. Science and technology are feeding the industry quite substantially, which has increased the codification of knowledge and facilitated international technology transfer (Paul, 1996). As a result of this, the industry has undergone a period of dynamic change in production methods and technologies, and new wine regions have emerged. During the 1990s, there was a process of catching up of new world producers (e.g. Chile, Argentina, South Africa, etc.) triggering a process of modernization among old world producers (e.g. Italy, France, Spain, Portugal) (see Smith, 2007). The study described in this paper involves a new world producer country (Chile) and a traditional wine producing country (Italy). From the end of the 1980s, both countries experienced processes of industry growth and modernization (Bell and Giuliani, 2007), which led to the emergence of new wine clusters.

Finally, the wine industry has another important characteristics that its firms are conceived of as very simple economic agents characterized by limited and stylized organizational forms. The interest in this study was to explore inter-firm relations, without considering intra-organizational functioning. This was possible, as firms in the wine industry tend to have a simple organizational structure, with most technical decision-making concentrated in a few people - typically the knowledge workers in the firm.

3.2 The data

This study is based on micro level data, collected at the firm level in two wine clusters – Colchagua Valley in Chile and Bolgheri/Val di Cornia in Italy - on the basis of interviews, carried out with the skilled workers (i.e. oenologists or agronomists) in charge of the production process at plant level in the firms in these clusters. The survey was based on a structured questionnaire and each interview lasted an average of one hour and a half. Interviews were carried out in 2002 and were addressed to the population of producers of fine wines in the two clusters, which numbered 41 in Bolgheri/Val di Cornia and 32 in Valle de Colchagua, making a total of 73 firms.

Despite being located in two very different countries, these two clusters share the important characteristics of having experienced a dynamic growth in the second half of the 1990s, both in terms of the quality of wine produced and in the extent to which they have started to become renown world-wide. For example, the number of times that each cluster has been cited annually by an international specialised journal like *Wine Spectator* has grown tenfold in the period 1994-2002 and in 2007 two wines of Bolgheri/Val di Cornia and one produced in Colchagua appeared among the Top 100 wines in the same wine journal (the author has documented this aspect in previous works, see e.g. Giuliani, 2005). In spite of this dynamism, however, at the time in which the interviews took place (2002), neither of these clusters could be considered as “hot spot” clusters, nor leaders in the world-wide process of technological change in the wine industry – unlike other areas (e.g. Napa Valley in California, or Bordeaux in France). For these characteristics, we find it plausible to consider these two clusters as being ‘emerging’ in the global panorama of wine production.

The two clusters also share other characteristics. They were of similar size (in both cases the overall areas are about 50 Km from north to south), and both densely populated by fine wine producers and grape growers. The vertical division of labour is rather shallow, with no other relevant suppliers located within the clusters’ territories. [3] Each cluster includes a business association, whose primary aim is the promotion of wines and the marketing of the local wine route but with no specific mandate to foster innovation and dissemination of technical knowledge. Instead, as documented by Giuliani (2007), these clusters are characterized by a rather intense inter-firm knowledge transfer at the horizontal level, through activities of informal joint problem solving or technical advice seeking/ giving by firms’ knowledge workers, namely the oenologists and enologists.

3.3 Operationalization of variables and method of analysis

3.3.1 Operationalization of variables

Dependent variable: Firm innovative output (*INNOVA*)

The dependent variable, innovative output (*INNOVA*), is a measure of the capacity of a firm to develop new wines, which are valued as “quality wines” by industry experts. Hence, it is a count variable that measures the average number of times a firm produced a high quality wine in the period 2003-2005, allowing a 1-3 year lag after the interviews (also consistent with McDermott et al., 2007).[4] The quality of worldwide wines is assessed annually, rated by national and international panels of experts whose

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[3] All the other linkages are outside the clusters – e.g. linkages involving universities, suppliers, clients, etc.

[4] The years indicated refer to the vintage of the wine, i.e., to the year of the grape harvest, not the year that the wine went on to the market. Wines need different aging periods before they are at their optimum for consumption.

ratings are listed in several specialized national and international wine journals and guides (e.g. *Wine Spectator*, *Decanter*, *Wine Enthusiast*, *Robert Parker's Guide*, etc.). Having a wine that is listed in any of these accredited wine publications is, first, an acknowledgement of the qualitative properties of the wines and second, acts as very powerful marketing device, since the experts' ratings strongly influence market prices (Nerlove, 1995; Combris et al., 1997).

The indicator of innovative output developed in this paper is based on *three* accredited wine journals: an international one, *Wine Spectator*, and a national one for each country: *Gambero Rosso* for Italy and the *Guia de vino de Chilevinos* in Chile.[5] The journals' ratings are based on the quality assessment of a panel of expert oenologists, who review several thousand wines each year in blind tastings. These oenologists assign a score to each wine brand according to a scale (most use a 100-point scale, where 50 indicates a poor quality wine and 100 indicates that the wine is of outstanding quality). Each rated wine is accompanied by information on the vintage, the wine area and the market price.

The indicator *INNOVA*, which is a count variable ranging from 0 to 6, was constructed as follows. For each firm, the average number of times that a wine was rated in an international or a domestic journal in 2003-2005 was counted, based on (1) the score attributed to the wine indicating very good quality (i.e. equal to or higher than 85 - the minimum threshold for very good wines in the *Wine Spectator* and *Chilevinos*' scales, or equal to or higher than 3 on the Italian scale); and (2) having an indicated price higher than the average price of the rated wines from each wine cluster.

The time period chosen (2003-2005) was based on the fact that, in the wine industry, the outcome of an innovative activity takes at least one year to materialize; it is necessary for a complete cycle of the vineyard to be completed (i.e. from the growth to harvesting of the grapes). In addition, in this industry time is required for any innovation to be appreciated in this industry; the results of minor adjustments to the wines may not be recognized until a year or more has passed. For this reason, the innovative output indicator was extended to 2005.

[5] National and international journals were considered to guarantee maximum coverage. Among the international publications, *Wine Spectator* was chosen as it provides the widest coverage (i.e. assesses the highest number of wines by country and vintage). The same criteria were applied to domestic sources.

To check that the variable *INNOVA* is a robust indicator of innovative output, we also used information, collected through the questionnaire, about respondents' view about other cluster firms' innovative performance (in terms of quality of wines and their market success). For each firm, we counted the number of times a firm was mentioned as being among the three 'top performers' of the cluster by the rest of the firms. Then, a reliability analysis of this measure against *INNOVA* was carried out resulting in a Cronbach's Alpha of 0.944, indicating a high degree of consistency between the two measures.

Independent variables

The independent variables are listed according to the order that the research hypotheses are formulated and tested in the paper.

Hypothesis 1: Firm knowledge base (*KB*)

The knowledge base of the firm (*KB*) is a factor of three variables, based on three sets of information collected through the questionnaire: (i) the number of technically qualified personnel (i.e. oenologists and agronomists) in the firm and their level of education and training; (ii) the experience of the firms' knowledge workers measured by months in the industry; (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. Intensity of experimentation was measured on a 0 to 4 point scale, according to the number of areas in which the firm experimented: e.g., if the firm experiments in all the production phases, from introduction of different clones or varieties in the vineyard "terroir", to management of the irrigation and vine training systems, fermentation techniques and enzyme and yeast analysis to final aging of the wine, it would score 4 for experimentation intensity. A firm involved in no in-house experimentation would score 0. As in Giuliani (2007), the three variables were transformed into a scalar value via Principal Component Analysis (PCA). Only one component was extracted, which explains more than 75 percent of the variance. A description of the components of this variable is reported in Appendix A.

Hypotheses 2-3: Degree of closure of a firm's ego-centred knowledge network (*NC)* **and degree of closure of a firm's ego-centred knowledge network, when all ties are strong** (*SNC*)

Both *NC* and *SNC* are calculated on the intra-cluster knowledge network, formed by horizontal linkages among wine producers for the solution of technical problems. In the questionnaire-based interview, these kinds of relational data were collected through a roster recall method (Wasserman and Faust, 1994), which means each firm was presented with a complete list (roster) of the other wine producing firms in the cluster, and was asked questions related to the transfer of innovation-related knowledge, as reported below:

Q1 *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 rate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none; 1= low; 2= medium; 3= high].

Q2 *Which of the following firms do you think have benefited from technical support from this firm?*
[Please rate the importance you attach to the knowledge linkage established with each of the firms according to its persistence and quality, on the basis of the following scale: 0= none; 1= low; 2= medium; 3= high].

These network data are expressed in matrix form. The matrix comprises *n* rows and *n* columns, corresponding to the number *n* of firms in each cluster. Each cell in the matrix reports the occurrence of knowledge being transferred from firm *i* in the row to firm *j* in the column. Since the relational questions (Q1 and Q2 above) allowed for the collection of "valued data" on the importance of innovation-related knowledge linkages, it was possible to construct a valued matrix for each cluster's knowledge network.[6]

[6] Q2 served to supplement the information derived from the replies to Q1. A relationship was considered to exist when either *i* or *j* declared its existence. The matrix based on Q2 was summarized by transposing the results from the matrix based on Q1. In the value matrix, the lower value of the two declared by *i* and *j* was used.

The matrices based on these data have specific characteristics. First, they include only knowledge linkages that are internal to the cluster. Second, the transfer of inter-firm knowledge analyzed in this study is specifically directed to the solution of technical problems or the transfer of technical know-how á la von Hippel (1987) because, in the contexts studied here, a firm's capability to achieve high wine quality and blends relies heavily on its technical skills and production methods. Third, due to the limited division of labour within these clusters, as discussed above, only horizontal linkages among fine wine producers are mapped by this survey. Wine producers reported vertical linkages, e.g. with suppliers of machinery, enzymes, chemicals, etc., but all external to the cluster. Vertical linkages with grape-growers within the clusters were not relevant as channels of knowledge, as growers did not appear to play a critical role in the innovation processes of these clusters. Thus, neither they, nor the local business associations which also do not play a role in the process of technological innovation, are included in the present study. The focus on horizontal knowledge linkages is consistent with numerous other studies that have highlighted their importance in innovation (e.g. von Hippel, 1987; Carter, 1989; Powell et al., 1996; Porter, 1998; Bouty, 2000).

Network closure (*NC*) was measured on the basis of the clustering coefficient. The clustering coefficient C_i for a vertex v_i is the proportion of links between the vertices within its neighbourhood divided by the number of possible links that could exist between them. This reveals the extent to which a firm's ego-network is formed by alters that are connected to each other. It ranges between 0 and 1, being 1 when alters are all connected to each other, and 0 when they are not. This coefficient is calculated on a dichotomous matrix, which includes all knowledge linkages existing between cluster firms. NC^2 is the squared term for *NC*. We choose to consider dichotomous data for *NC* and NC^2 because valued data are considered in the measurement of strong network closure below.

Strong network closure (*SNC*) was also calculated through the clustering coefficient, but was based on a dichotomous matrix that included only strong knowledge linkages – i.e. linkages with a value higher than 1 in questions Q1 and Q2. All network computations were based on UCINET (Borgatti et al., 2002). SNC^2 is the squared term for *SNC*.

Hypothesis 4: Firms bridging structural holes in the local knowledge network (*SHOLE*)

This indicator measures the extent to which a firm spans structural holes in the intra-cluster knowledge network. This variable is measured using the same matrices as used for the measurement of network closure (i.e. on the basis of the matrices constructed from the responses to Q1 and Q2 above). The measure of access to structural holes (*SHOLE*) is calculated as 1 minus the firm's *constraint* score (in cases where the *constraint* was non-zero) and 0 for all other cases, because a zero score arose only when the firm was unconnected to others, and thus had no access to structural holes.

Constraint is the firm's lack of access to structural holes. Consistent with Burt (1992) and Zaheer and Bell (2005), we measure this as:

$$Constraint = x_{(ji)} + \sum x_{(iq)} * x_{(jq)},\ q \neq i, j \text{ (Burt, 1992, p. 54)}$$

where $x_{(ji)}$ equals the number of direct ties from *j* to *i* and $\sum x_{(iq)} * x_{(jq)})$ is the sum of indirect ties from *j* to *i* via all *q*. we used a symmetric dichotomous matrix for this purpose. Network computations are based on UCINET (Borgatti et al., 2002).

Hypothesis 5: External openness (*EXTOPE*)

External Openness is defined as the variety of extra-cluster sources of knowledge a firm relies in its innovative activities. The questionnaire included a set of questions exploring the sources of extra-cluster knowledge used by the firm in the two years prior to the interview. These sources fell into ten categories: (i) universities and public research laboratories; (ii) other public institutions; (iii) suppliers; (iv) clients; (v) other firms outside the cluster – including the headquarters when the firm is foreign; (vi) business associations and consortia; (vii) domestic consultant; (viii) foreign consultant; (ix) private laboratories and (x) other sources.[7]

[7] It would have been interesting to look at the effect of each single source of extra-cluster knowledge, as e.g. in McDermott et al. (2007). However, parsimony in the estimation model renders the use of a composite indicator

On the basis of Laursen and Salter (2006), each of the ten sources is coded with a binary variable where 0 indicates no use and 1 indicates use of a given knowledge source. According to these criteria, the value of a firm's external openness could range from 0 in the case of no linkages with extra-cluster sources of knowledge, to 10 when the maximum possible extra-cluster interconnection was achieved by the firm for all categories. This value was normalized on a 0 to 1 scale. Thus, a value of 0.50 means that the firm is using 50 percent of all possible extra-cluster knowledge sources. $EXTOPE^2$ is the squared term for *EXTOPE*.

Control variables

The estimations were carried out using a number of control variables for influences on the innovative output of firms. These were:

- size of the firm, measured by the log of employees (*LEMP*);
- age of the firm, measured as the number of years since the start of operations, to 2002 (*AGE*);
- ownership, which is a dummy variable indicating whether the firm is foreign- (1) or domestic-owned (0) (*OWN*);
- type of organization since firms in the clusters have three different types of organizational structures: *ORG1* corresponds to firms that are part of a national group and perform all phases of the production process within the cluster; *ORG2* are firms that are part of a national group, but perform only part of the production process, usually grape-growing, within the cluster; *ORG3* refers to firms (foreign or domestic) that are independently owned and that perform all production phases in the cluster in which the headquarters is also located;
- location of the cluster (*DCOUNTRY*), which controls for differences in the climatic conditions and industry characteristics of Chile and Italy. This variable takes the value of 0 for Chile and 1 for Italy;

more desirable here. Also, this approach is consistent with other previous works on a similar subject (e.g. Laursen and Salter, 2006).

- a dummy variable was introduced to control for start-up firms, which in the year of the interview, were in the process of planting their entire vineyards from scratch (*DSTART*). This meant that they would not be in a condition to launch any wine on the market for at least three years – i.e. the time needed for a vine to produce grapes that would make wine of drinkable quality. This dummy takes the value 1 in the case in that the firm is in the start-up conditions described above, and 0 otherwise.

3.3.2 Estimation method

We adopted a Negative Binomial (NBin) estimation, which was necessary because the dependent variable *INNOVA* takes non-negative count values characterized by overdispersion (Cameron and Trivedi, 1986). The variance in *INNOVA* (3.83) is in fact almost three times greater than the mean (1.56). This variable, moreover, has a high number of zeros and the proportion of firms with a specific positive value decreases as the value of the count increases. The estimations were carried out on aggregate data, obtained by pooling the variables for the two clusters. Given the fact that the data are from two different populations of firms (i.e. from an Italian and a Chilean cluster), the estimation controls for the possibility that random disturbances in the regression are correlated within groups. As suggested by Moulton (1990), it is reasonable to expect that units with observable common characteristics, such as location, also share unobservable characteristics, which lead to spurious results in estimations of the effects of aggregate variables on micro units.

It is necessary to introduce a caveat in relation to endogeneity resulting from reverse causality, of the models adopted to test these hypotheses. Theories within the economics of innovation do consider the relationship between the innovative output and several of its inputs (in this specific case, the knowledge base of a firm, and the existence of linkages) as being dynamically related, making it extremely difficult to state where causality lies. Even if it does not solve the problem, in this paper, a lagged dependent variable is used to control for this type of endogeneity and the independent variables are considered to be predetermined with respect to the dependent variable. Also, note that the hypotheses are formulated as to look for relationships among variables, rather than strict causality.

4 EMPIRICAL RESULTS

4.1. Results of the estimations

Table 1 presents descriptive statistics for the cluster variables and correlation matrices obtained from pooling the data. As expected, network closure and strong network closure are correlated (the coefficient is 0.64), while both are uncorrelated with the measure of structural holes – reflecting the fact that they represent two opposite network effects.[8] Table 2 reports the results for the econometric estimations used to test the research hypotheses.

Model 1 in Table 2 includes only the control variables for the regression. It shows that size (*LEPM*) is positively related to innovative output and that foreign firms (*OWN*) located in the clusters are more likely to have higher innovative output. It also shows that younger firms are more innovative than older ones, controlling for young firms whose vineyards are not yet producing wine (*DSTART*). Finally, the type of organization influences the innovative output – with *ORG1* and *ORG3* being significant and negatively related to the dependent variable.

[Table 1 about here]

[Table 2 about here]

Model 2 in Table 2 tests Hypothesis 1. The regression shows that *KB* has a positive coefficient (0.61) significant at 1 percent. In line with the literature (e.g. Zaheer and Bell, 2005), this result suggests that the knowledge accumulated by a firm via the skills of its knowledge workers and its experimentation efforts, is related to its innovative output. Hypothesis 1 is therefore supported. It is worth noticing that in this model, foreign firms persist being more innovative than domestic ones. Given the significance

[8] However, we do not find negative correlation because of the presence of isolated firms, which take the value of 0 in both types of indicators.

and the relevance of this result, Model 2 will be used as the baseline model to test the remaining hypotheses.

Model 3 in Table 2 tests Hypothesis 2 and explores the relationship between the degree of closure of a firm's ego-centred knowledge network (*NC*) and its innovative output. In the estimation, the coefficient for *NC* is positive (2.16) and strongly significant (at 1%), while NC^2 is negative (-2.84) and significant at 5 per cent, indicating a non monotonic relationship, which is consistent with an inverted U-shape. This evidence provides support to Hypothesis 2.

Model 4 in Table 2 tests Hypothesis 3 regarding the relationship between the degree of closure in a knowledge network of strong ties (*SNC*) and *INNOVA*. We find a non-significant effect of both *SNC* and SNC^2 variables. Given the low correlation coefficients of these variables with *INNOVA* (Table 1), this result is not entirely surprising. Hypothesis 3 is therefore not supported. Of interest here, is that, in spite of not being significant, the coefficient for *SNC* in the estimation has a negative sign (-1.11).[9]

Model 5 tests Hypothesis 4 regarding the relationship between the degree to which a firms bridges structural holes in the intra-cluster knowledge network (*SHOLE*) and *INNOVA*. As shown in Table 2, the variable *SHOLE* is not significant: the coefficient is 0.67 with a robust standard error of 1.05. Hypothesis 4 is therefore not supported by this statistical evidence, indicating that this type of structural position has no influence on the innovative output of cluster firms.[10]

Model 6 in Table 2 tests Hypothesis 5, which explores the effect of external openness on the innovative output of firms. We include variables *EXTOPE* and $EXTOPE^2$ to test for the non monotonic effect on innovative output. We find that *EXTOPE* is positively related to the dependent variable *INNOVA* (the coefficient is 0.21 with a robust standard error of 0.05, significant at 1%), suggesting

[9] We also tried a model where *SNC* and SNC^2 were added up to Model 3, but results did not change significantly.
[10] Results do not change when controlling for isolated firms.

that the more a firm is open to diverse sources of extra-cluster knowledge, the more it innovates. Also the squared term *EXTOPE*^{2} has a negative and significant coefficient (the coefficient is -0.01 with a robust standard error of 0.002 significant at 1%), indicating that this variable has a non monotonic shape and thus supporting Hypothesis 5.

Model 6 reports the best model, indicated as the best fit, considering the variables that we included in the study. It shows that, when we account for external openness, ego-network closure is no longer significant, whereas *KB* maintains its positive and significant effect.[11] When *KB* and *EXTOPE* are controlled for, the size of the coefficient on *NC* decreases significantly, while *EXTOPE* does not change in any significant way.

4.2. Robustness checks

We carry out robustness checks on the variables that show a significant and non monotonic relationship with the dependent variables, namely *NC* and *EXTOPE*, by looking at whether they could take a different non linear shape, such as the logarithmic. We hence develop a Model 3-log, which is the same as Model 3 (Table 1), but where *NC* and *NC*^{2} are replaced with the log of *NC*. We find that the coefficient for the log of *NC* is positive and significant (0.41 significant at 1%), while the remaining variables do not change significantly. The Log-likelihood in Model 3-log is sensibly higher (-107.48), than in Model 3 (-107.31), indicating that the latter (Model 3) fits data better than the former, preserving the validity of our results.

As concerns *EXTOPE* we develop a Model 6-log where we the replace *EXTOPE* and *EXTOPE*^{2} with the log of *EXTOPE*. Also in this case, we find that the coefficient is indeed positive and significant (1.87 at 1%), while the rest of the results are not altered. More importantly, however, we find that Model 6-log fits slightly better the data, as its Log- likelihood is of -102.76, thus lower than the one for Model 6 (102.98). We then run a different model, called Model 8, where we include *NC* and *NC*^{2}

[11] What these results could also suggest is the presence of omitted variable bias in Model 3. *EXTOPE* and *NC* are positively correlated (coefficient is 0.45) and both have positive explanatory power for firms' innovative output. Hence, failing to include *EXTOPE* in the specification could lead to an upward bias in the coefficient of *NC*.

and the log of *EXTOPE*. We obtain that the coefficient of *NC* decreases significantly and becomes non significant like in Model 7 (the coefficient is 0.60 with a standard error of 0.69). All the other variables are not altered, while the log of *EXTOPE* is significant and positive (coefficient is 1.78 significant at 1%). The key result here is that Model 8 has a slightly lower Log-likelihood (102.52) than Model 7 (-102.74), indicating that the impact of *EXTOPE* on *INNOVA* is more proximate to a logarithmic than to an inverted U shape – although both are significant.

We also explore the non linear behaviour of *NC* and *EXTOPE* using Generalized Additive Models (GAM) (Hastie and Tibshirani, 1990), which have been increasingly more applied in social sciences to estimate non-parametric functions of the predictor variables through the use of scatterplot smoothers (see Beck and Jackman,1998 for a discussion). We find results that confirm the estimations above: *NC* behaves more like an inverted U-shape, whereas the impact of *EXTOPE* on *INNOVA* is non linear but hardly non monotonic, being concave and reaching a sort of plateau after a certain level of the variable. However, it should be mentioned that, whereas GAM estimations allow the use of the family of negative binomial (Wood, 2006), they do not allow the calculation of robust standard errors – which is appropriate for this type of geographically bounded data (Moulton, 1990). For this reason, GAM estimations are not fully reported here and are used only as a check to visualise the behaviour of the variables without imposing a parametric function.[12]

5. DISCUSSION AND CONCLUSION

This paper makes a significant step ahead in understanding the drivers of innovation in industrial clusters and in analysing the role of local network embeddedness, using more rigorous analytical methods than achieved by previous cluster studies. An important novelty of this paper is that it tries to bring to the attention of management scholars clusters that are not “hot spots” in the global landscape, but that are making an effort to compete in the international markets and could then become a threat for established clusters.

[12] Results of GAM estimations and plots are available upon request.

To explore the relationship between local embeddedness and innovation, we use three measures of firms' structural positions (i.e. network closure, strong network closure and structural holes) and we find that there are benefits of network closure for innovation but these are subject to decreasing returns, so that there is a point where additional network closure becomes unproductive. One possible interpretation of this result is that, as firms become part of stable and close local knowledge networks, they incur a series of networking costs that outweigh the advantages in terms of any new knowledge or solutions to problems the network might offer. It is plausible that strong closure in a firm's ego-network generates expectations in terms of reciprocity in knowledge transfer, as well as a sharing of some of the secrets of the job among closely-knit firms. In such cases, firms no longer benefit from this type of embeddedness. Also, as suggested by Gargiulo and Benassi (2000), network closure may lead firms to become "trapped in their own net" (p. 183), when they have no other source of knowledge other than the network in which they are embedded. This interpretation is also consistent with the negative sign of strong network closure, although the coefficient was not significant. In contrast, the fact that firms do not take advantage from bridging structural holes may relate to the very narrow scope of the knowledge sources within the cluster studied, all represented by wine producers operating within the same territory. These sources may not be capable of generating (and transferring) knowledge that is truly diverse or to spark real creativity within the network.

More importantly, however, this paper finds that the role played by firms' internal knowledge bases and their external openness is more significant than intra-cluster network closure in explaining firms' innovation in these two emerging clusters. Our finding that a firm's knowledge base is a key driver of innovation output in cluster firms is in line with innovation research, which for a long time has stressed the path-dependent nature of innovation, and the importance of the accumulation of knowledge for the generation of new knowledge (Nelson and Winter, 1982; Grant, 1996; Bell and Zaheer, 2005). Also, this paper contributes to the growing body of cluster studies that is giving more consideration to the role played by firms' extra-cluster linkages. Slightly differently from Laursen and Salter (2006), we find for low levels of external openness the impact on innovative output does increase rapidly, whereas, after a certain level of external openness, the marginal increase tends to be minimal (i.e. as in a logarithmic function).[13] These results reinforce the view that, when firms and clusters compete on a global scale, their interconnection with sources of knowledge outside the cluster boundaries – at both national and international levels- is critical to access diverse ideas and to nurture the innovation process, and that this can be the real structural holes' bridging.

These results seem to indicate that research on clusters may have overemphasized the critical role of local embeddedness in explaining the innovative performance of cluster firms. While this result would seem to contradict most of the established literature on the success of industrial clusters, we believe this is a plausible result in emerging clusters, which are not established "hot spots" in the world economy. We agree in fact that, in "hot spots" clusters, some form of embeddedness in local knowledge networks may play a significant role in explaining innovation, precisely because an important part of the capabilities needed to develop world-level innovations is located within the cluster itself. However, if one looks beyond such "hot spots", it seems to us that the way through which a firm manages to be innovative, may have more to do with other aspects of individual firms and their alters – e.g. their internal knowledge bases and their external openness – than with the degree and nature of their local embeddedness. In fact, stable and close networks may become real traps, if they are established with firms characterized by both weak knowledge bases and low external openness.

On this basis, it is plausible that managers working in vibrant, leading clusters, such as Silicon Valley, agree that local 'networking' is a good thing (Saxenian, 1994) and that, to maximise the benefits that a cluster can offer, they must participate actively and establish a significant local presence (Porter, 1998). However, our recommendation is not directed to them. It is directed to the vast majority of managers, who are not working in "hot spots", but yet aim at transforming their environment into a thriving economy. To them three recommendations are made here. First, they should think about fortifying their firm's internal capabilities, though e.g. the hiring/training of knowledge workers and

[13] In the GAM estimation the level of external openness, at which the marginal impact started to reach a sort of plateau, was around 0.45, which indicates firms using about half of the possible extra-cluster sources of knowledge. However, for the reasons explained earlier this data needs to be taken with caution.

the development of significant research and development or experimentation activities. Second, they should look beyond the local context, establishing extra-cluster linkages with relevant sources of knowledge. Third and last, they should avoid being over-embedded at the local level, by e.g. trying to be selective in the formation of knowledge linkages with other cluster firms.

Limitations and further research

This analysis was set within specific empirical and methodological limits. The first was that this is a single industry study. The generalization of results is therefore bounded by the specificities of the wine industry and of the two clusters. In particular, this industry is characterized by rather incremental innovation by cluster firms, which can allow the diffusion of proprietary knowledge without problematic competitive backlash effects (Carter, 1989). This leads to the formation of intra-cluster knowledge networks in this specific industry, which may take different conformations in other industries. Furthermore, wine production, similar to other agricultural activities, relies quite heavily on external knowledge, and particularly on applied research by universities and suppliers' R&D laboratories, which may explain the critical role of extra-cluster linkages in this study. These features may not be characteristic of other industries.

The second limitation refers to the operationalization of the concept of embeddedness, which here was based on only one type of network – i.e. the intra-cluster knowledge network. Cluster scholars should develop this aspect further and focus on the structural embeddedness of firms in more than one network, including pure social networks (e.g. kinship, friendship), and vertical business networks. Also, the focus on knowledge networks was biased toward the more technological forms of innovation and other studies might want to pursue innovation-related knowledge in other areas (e.g. marketing, branding etc.). The focus in this study on technical knowledge is due to the fact that, at the plant level, technical changes are what drives changes in the quality and characteristics of wines and wine blends.

Finally, the third limitation has to do with the operationalisation of the concept of innovative output. Measuring innovative output on the basis of the quality assessment of firms' wines made by experts in the industry is certainly problematic. First, because it uses a very narrow definition of innovation, based on the intrinsic quality of the wines and not on their market success or on the economic performance it might lead to. Second, because we have to make the assumption that a wine rated positively by wine experts constitutes an innovation with respect to existing wines. These concerns are however mitigated by the fact that the indicator of innovative output matches almost perfectly with the respondents' view about other cluster firms' innovative performance (in terms of quality of wines and their market success), as explained at Section 3.3.1. Furthermore, it is also worth mentioning that, in this specific industry, a high rating given by experts is typically the result of a significant and continuous process innovation, and that it also reflects a value on the market – in terms of e.g. higher prices. Also, these types of data have the important advantage of being lagged in time and of being totally exogenous with respect to the process of data collection. Having said this, it would certainly be useful to have further research using more fine-tuned innovative output indicators.

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Appendix

A. Firm knowledge base

The knowledge base of the firm (KB) has been measured by applying a Principal Component analysis to the following three 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'. 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 realized in the wine industry only.

Variable 3: 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 three activities of the productive chain are subject to experimentation initiatives.
- (4) when all of the activities in the productive chain are involved in some experimentation project.

Principal Component Analysis extracted one component, which we adopted as a measure of firm knowledge base (*KB*).

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Table 1 Descriptive statistics by clusters and correlation matrix

	Variables	Descriptive statistics by cluster						Correlation Matrix														
		Valle de Colchagua			*Bolgheri Val di Cornia*																	
		Min	*Max*	*Mean (SD)*	*Min*	*Max*	*Mean (SD)*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	***INNOVA***	0	6	1.56 (1.95)	0	6	1.24 (1.78)	1.00														
2	***KB***	-1.13	3.01	0.00 (1.00)	-0.77	3.46	0.00 (1.00)	0.53***	1.00													
3	***NC***	0	0.50	0.17 (0.16)	0	1.00	0.17 (0.26)	0.27**	0.26**	1.00												
4	***NC^2***	0	0.11	0.02 (0.03)	0	0.68	0.07 (0.16)	0.02	0.05	0.75***	1.00											
5	***SNC***	0	0.50	0.06 (0.12)	0	1.00	0.14 (0.31)	0.09	0.21*	0.64***	0.55***	1.00										
6	***SNC^2***	0	0.15	0.016 (0.03)	0	0.79	0.10 (0.23)	0.03	0.13	0.56***	0.62****	0.92***	1.00									
7	***SHOLE***	0	0. 82	0.45 (0.33)	0	0.83	0.32 (0.31)	0.34***	0.35***	0.05	-0.13	-0.30	-0.05	1.00								
8	***EXTOPE***	0	0.40	0.24 (0.12)	0.07	0.57	0.23 (0.12)	0.56***	0.67***	0.45***	0.11	0.25**	0.13	0.39***	1.00							
9	***$EXTOPE^2$***	0	0.06	0.01 (0.02)	0	0.11	0.01 (0.02)	0.22*	0.41***	0.04	0.08	0.05	0.03	0.08	0.35***	1.00						
10	***LEMP***	0.69	5.99	3.46 (1.13)	0	4.61	1.41 (0.92)	0.41***	0.41***	0.14	-0.07	0.01	-0.09	0.25	0.26**	0.22*	1.00					
11	***AGE***	3	104	22.38 (28.51)	1	154	24.07 (29.68)	-0.01	0.01	0.07	0.23**	0.07	0.15	-0.01	-0.09	0.24**	0.21*	1.00				
12	***OWN***	0	1	0.18 (0.39)	0	1	0.02 (0.15)	0.19	0.03	0.13	-0.03	-0.06	-0.09	0.18	0.19	0.00	0.14	-0.18	1.00			
13	***ORG1***	0	1	0.22 (0.42)	0	1	0.07 (0.03)	0.17	0.35***	0.17	-0.04	0.04	0.06	0.09	0.36***	0.16	0.29**	-0.12	0.41***	1.00		
14	***ORG3***	0	1	0.66 (0.48)	0	1	0.93 (0.26)	-0.18	-0.30**	-0.17	0.09	0.00	-0.01	-0.26**	-0.34***	-0.10	-0.37***	0.03	-0.31**	-0.82***	1.00	
15	***DSTART***	0	1	0.03 (0.17)	0	1	0.07 (0.26)	-0.19	0.08	0.00	-0.02	-0.11	-0.07	0.04	0.23**	0.12	-0.10	-0.13	0.13	0.08	-0.04	1.00

Table 2 Negative binomial estimations with robust standard errors

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	CONTROLS	**(HP 1)**	**(HP 2)**	**(HP 3)**	**(HP 4)**	**(HP 5)**	**Best Model**
KB		0.61*** (0.05)	0.52*** (0.05)	0.64*** (0.10)	0.54*** (0.019)	0.18*** (0.01)	0.17*** (0.01)
NC			2.16*** (0.14)				0.57 (0.62)
NC^2			-2.84** (0.29)				-1.23** (0.62)
SNC				-1.11 (2.93)			
SNC^2				0.99 (3.84)			
SHOLE					0.67 (1.05)		
EXTOPE						6.22*** (1.39)	5.93*** (0.59)
EXTOPE^2						-10.54*** (0.26)	-9.66*** (0.21)
Control variables:							
LEMP	0.53*** (0.20)	0.17 (0.148)	0.14 (0.11)	0.20 (0.22)	0.16 (0.19)	0.15*** (0.24)	0.15*** (0.02)
AGE	-0.7e-2*** (0.1e-2)	-0.4e-2 (0.5e-2)	-0.3e-2 (0.7e-2)	-0.4e-2 (0.6e-2)	-0.4e-2 (0.6e-2)	-0.2e-2 (0.5e-2)	-0.2e-2 (0.7e-2)
OWN	0.78*** (0.09)	0.81*** (0.08)	0.80*** (0.26)	0.83*** (0.06)	0.74*** (0.07)	0.57** (0.23)	0.59** (0.27)
ORG1	-0.59*** (0.06)	-0.95*** (0.21)	-0.78*** (0.19)	-1.01** (0.42)	-0.73 (0.69)	-0.62*** (0.03)	-0.60*** (0.07)
ORG3	-0.59*** (0.13)	-0.51*** (0.19)	-0.30 (0. 20)	-0.54* (0.33)	-0.31 (0.54)	-0.17*** (0.05)	-0.13 (0.11)
DSTART	-15.94*** (1.00)	-16.51*** (1.11)	-15.28*** (1.00)	-15.96*** (1.21)	-15.34*** (1.14)	-15.64*** (0.1.12)	-15.84*** (1.08)
DCOUNTRY	0.82** (0.37)	0.05 (0.30)	0.03 (0.14)	0.11 (0.35)	0.12 (0.25)	0.05 (0.10)	0.08*** (0.00)
Constant	-0.70 (0.57)	0.42* (0.22)	0.00 (0.13)	0.41*** (0.16)	0.00 (0.38)	-1.29*** (0.27)	-1.37*** (0.06)
Log- PseudoL	-113.72	-109.17	-107.31	-108.83	-108.50	-102.98	-102.74
Valid N	73	73	73	73	73	73	73

Note: Robust standard errors in brackets. *** Significant at 1%; ** Significant at 5%; * Significant at 1%.