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Family firm network strategies in regional clusters: evidence from Italy

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Abstract Knowledge networks in regional clusters are fundamental to support innovation and local development. Within clusters, family firms are key in creating business opportunities and supporting the establishment of inter-organizational networks. Yet, their role within regional clusters for knowledge transfers is still not well understood, especially in comparison with non-family firms. This paper applies Exponential Random Graph Models (ERGMs) to network data collected from the Parabiago cluster, one of the most important Italian footwear clusters, to contribute to a better understanding of the network strategies of family firms. We identify distinct network strategies associated with the cluster firms, accounting for different knowledge exchange types: technological, market, and managerial. In our modelling, we control for firm-level attributes and dyadic-level attributes, such as geographical distance and cognitive proximity between cluster firms. Our results suggest that the proneness of family firms to grow networks is highly robust relative to non-family firm relationships, irrespective of knowledge types being exchanged. Moreover, family firms tend to establish connections with other family firms, showing the presence of homophily in their networking approach; however, non-family firms are rather different, since they do not have the same homophilous approach when it comes to exchange knowledge with other non-family firms. These results indicate that the nature of ownership is driving knowledge exchange differences. This key feature of family-only relationships in clusters may help managers and policymakers in devising more effective and targeted cluster strategies.

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Plain English Summary Family firms are key in supporting local development, especially in regional clusters. However, while it is well established that their strategies differ from other (non-family) firms, it is still unclear what is their networking behaviour for supporting knowledge exchange—and thus innovation. This paper provides an empirical overview of this phenomenon, by analyzing an Italian case study: the Parabiago footwear cluster. The results show that (a) family firms are more proactive in establishing network relationships; (b) family firms tend to exchange knowledge with other family firms, while non-family firms do not show the same homophilous approach. Overall, this indicates that policies for clusters need to balance support for distinct business types and recognize the familiness characteristics of regional productive structures.

Keywords Knowledge network · Family firm · Regional cluster · Social Network Analysis · ERGM

JEL Classification O31 · R11 · R12

1 Introduction

Knowledge exchange is widely recognized as one of the main factors supporting innovation and economic growth, allowing firms to access complementary resources that are not available internally (Gulati & Gargiulo, 1999; Marra et al., 2020; van Wijk et al., 2008). In regional clusters, inter-organizational knowledge networks have been found to be key for supporting innovation, overcoming physical and cognitive barriers and supporting knowledge diffusion (Ferretti et al., 2021; Giuliani & Bell, 2005; Sammarra & Biggiero, 2008).[1]

Family firms are effectively contributing the success of regional clusters. This is because they are strongly embedded in the local business ecosystem (Pittino et al., 2021) and they play an important role in both the industrialization and internationalization of the countries in which they operate (Coli & Rose, 1999; Mariotti et al., 2021). Family firms are influenced by the structure of the local economic and institutional environment (Basco & Bartkevičiūtė, 2016; Bjuggren & Sund, 2002; González & González-Galindo, 2022; Ricotta & Basco, 2021); at the same time, they are also able to influence the local context in which they operate (e.g. Bichler et al., 2022). This is evident in regional clusters, where tacit knowledge exchange and informal rules result from interactions of firms sharing similar values, such as those led by families with strong connections with the local territory (Basco & Bartkevičiūtė, 2016). Taking the knowledge-based view of the firm, Zahra et al. (2007) demonstrated that formal and informal knowledge-sharing practices are positively associated with the strength of family firms' technological capabilities. Moreover, evidence from Germany suggests that networks are key innovation drivers, as part of corporate entrepreneurship in family firms (Weimann et al., 2021). The involvement of family firms in knowledge networks enables the discovery of novel entrepreneurial opportunities (e.g., Sciascia et al., 2013); at the same time, these firms are inherently different from non-family firms in their entrepreneurial approach, as discussed by De Massis et al. (2013), Feranita et al. (2017), and Ardito et al. (2019).

Despite the number of studies focusing on family firm networking, the literature on network strategies adopted by family firms in regional clusters is still limited. Moreover, Block and Spiegel's (2013) contention that these strategies deserve further investigations remain pressing, as also suggested by the review of Zellweger et al. (2019). Most of the studies investigating this phenomenon (e.g. Gurrieri, 2008; Mathews & Stokes, 2013; Pucci et al. 2020) concentrate on the main differences between family and non-family firms. However, these studies did not focus on the different types of knowledge exchanged between these firms. Providing empirical evidence on the networks established between family and non-family firms is relevant for researchers and policymakers interested in family business, because it clarifies what knowledge-transfer strategies are adopted by family

[1] Similar to Giuliani (2007), we use the notion of regional clusters, industrial districts, industrial clusters, and industrial agglomeration interchangeably throughout this paper. We note that the management literature has focused on the determinants of knowledge transfer, distinguishing three common network types: intra-corporate networks, strategic alliances, and industrial districts (Inkpen and Tsang 2005). In contrast, the industrial cluster literature has focused on geographical agglomerations of organizations operating in the same industry (Humphrey and Schmitz 1996).

firms compared to non-family firms, and what drives these different strategies. The objective of our study is to fill this gap, by investigating family and non-family firm relationships while accounting for different types of knowledge exchange networks. More specifically, we contribute by analysing the endogenous network mechanisms characterizing a regional cluster, as these mechanisms are multifaceted and not limited to one single firm typology. We therefore not only contribute to explore in depth the innovation context of family firms (Lattuch, 2019), but we also advance our understanding of corporate strategies in regional clusters. To be innovative and competitive, firms need to find ways to interact with their local competitors: in this study, we investigate which options are preferred. For this purpose, we also try to integrate the literature on family firms and knowledge networks in regional clusters and assess three types of informal knowledge exchange—namely technological, market, and managerial knowledge—in the context of Parabiago, one of Italy's economically most important footwear cluster. Our empirical results show that family firms have a different networking behavior compared to non-family firms: overall, family firms are more prone to exchange knowledge, especially with other family firms. On the other hand, non-family firms do not have such homophilous approach—i.e., they do not have a preference to establish connections with other non-family firms. These findings confirm what was observed by De Massis et al. (2013), Ardito et al. (2019), and Duong et al. (2022) when analyzing the strategic behavior of family and non-family firms. At the same time, we advance this stream of literature by disentangling the relationships between family and non-family firms in the context of knowledge exchange—and we argue that these distinct relationships can have an impact on regional clusters. The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on family firms and knowledge networks in regional clusters. Data and methods are presented in Sect. 3, followed by Sect. 4 presenting the results of the analysis. Finally, Sect. 5 concludes addresses limitations and provides policy implications.

2 Literature

Inter-organizational relationships are influenced by organizations' knowledge base, absorptive capacity, prestige, and proximity (e.g. Belso-Martínez et al., 2016), which can channel resources through organizations' network experience and repeated interactions (Oliver & Ebers, 1998; Podolny & Page, 1998). When organizations interact, they create opportunities to learn from each other: as a consequence, social capital is built to achieve specific targets and potential benefits for all (Gulati & Gargiulo, 1999; Leppäaho et al. 2018; Whittington et al., 2009).

Evidence from economic geography suggests that regional clusters are particularly supportive for the establishment of inter-organizational relationships (e.g. Cooke, 2002). In this vein, Giuliani (2007, p. 142) argued that "the emergence of successful clusters or districts has become increasingly associated with the presence of localised networks, based on market and socio-institutional relationships among cluster firms." Cluster firms have a variety of strategies when it comes to establishing network relationships (Juhász & Lengyel, 2018; Tallman et al., 2004); moreover, the success of regional clusters is mainly attributed to the presence of knowledge spillovers emerging from these relationships (Easterby-Smith et al., 2008; Iammarino & McCann, 2006). However, as pointed out by Juhász (2021), knowledge is not available for all actors working in regional clusters. Many authors described the idiosyncratic nature of inter-firm knowledge exchange, and the fact that knowledge is selectively and unevenly exchanged in regional clusters (Alberti & Pizzurno, 2015, 2017; Belso-Martínez et al., 2017; Boschma & ter Wal, 2007; Giuliani, 2010). In this respect, Sammarra and Biggiero (2008) explored how firms engage in the exchange of different forms of knowledge—technological, market, and managerial knowledge—and they discovered that a more intense exchange of technological knowledge occurs in high-tech clusters.

However, in spite of the significant literature on knowledge networks, their antecedents, and the impact they have on regional clusters, a narrower focus on the types of actors establishing these networks is largely missing. Previous studies investigated the behavior of spinoffs and start-ups (Alberti & Pizzurno, 2017; Juhász, 2021). Yet, a focus on family firms seems also desirable, since family firms are essential in regional clusters: because of their social ties, they are capable of influencing entrepreneurial networks and creating business opportunities (Bichler et al., 2022). Indeed, family firms exhibit peculiar networking strategic approaches (see the *Entrepreneurship Theory and Practice* special issue organized by Zellweger et al., 2019), since their interactions are aimed towards the implementation of business models where knowledge resources are central (Clinton et al., 2018; Su & Daspit, 2021). The aforementioned special issue from Zellweger et al. (2019) included papers which explored in depth how family firms establish inter-firm connections. For example, the work of Lude and Prügl (2019) demonstrated that family firms own a reputation of being trustworthy, and therefore they are able to relate to other stakeholders using reputation as an intangible asset—similarly to what happens with social capital. Other empirical evidence comes from the work of Baù et al. (2019), which illustrated how family firms benefit from local embeddedness and their interest in nurturing special relationships with local actors because of their nonfinancial goals. Hence, we hypothesize that:

> H1: In regional clusters, family firms are more prone to establish network relationships than non-family firms.

The empirical evidence suggests a distinct involvement of family and non-family firms in inter-organizational networks. The review of De Massis et al. (2013) pointed out that the propensity to search for external knowledge varies between family and non-family firms. The ability to create long-term relationships with other stakeholders is a peculiar characteristic of family firms, and it enables them to design innovative activities that cannot be replicated by non-family firms. According to Feranita et al. (2017), inter-organizational relationships are particularly relevant for family firms, which rely on external knowledge to be innovative and surviving in competitive markets. As illustrated by Soleimanof et al. (2018) and Arregle et al. (2007), family firms strongly rely on social capital and the capacity to establish long-term relationships with other actors; non-family firms are more prone to develop short-term relationships. Ardito et al. (2019) suggested that family firms are in a better position for engaging in collaborations and alliances compared to non-family firms because of two reasons: their distinctive traits in terms of ownership and management, and their focus on non-financial objectives. The same authors argued that "family firms differ from nonfamily ones in their ability to exploit resources that are geographically bounded and establish R&D relationships with localized organizations because they often present embeddedness within the cultural and socioeconomic local context in which they arose and grew" (Ardito et al., 2019, p. 186). Recent studies demonstrated how the nature of family firms leads to specific open innovation practices. In a case study of a high-teach Italian family firm (Casprini et al., 2017), it was observed that imprinting and fraternization are two typical family firm-related processes through which the firm creates a unique approach to managing external networks. Such processes promote trust and value sharing, end enable the firm to access local resources. This was highlighted also by Lambrechts et al. (2017), which argued that family firms select partners that can be trusted. If non-family firms are perceived as less trustworthy, family firms will not develop relationships with them: they will probably show a preferential attachment for other family firms. In light of the above evidence, we anticipate the existence of differences in the network strategy of family and non-family firms. This leads us to formulate the following hypothesis:

> H2: In regional clusters, family firms tend to establish homophilous interfirm relationships with other family firms.

3 Empirical setting

3.1 Data

In this study, we analyze data from the footwear cluster of Parabiago (Italy), which is characterized by the presence of firms operating along the entire footwear value chain. Parabiago is a municipality of around 30,000 inhabitants close to the main urban centre of Milan (Italy), and it has a long tradition in the footwear industry. The first company started to operate at the end of the nineteenth century, and in the last decades, multinational companies outsourced part of their production to most of the firms located in this area (Cainelli & Zoboli, 2004).

Before starting the data collection process, we proceeded with the identification of the Parabiago cluster firms. We were supported by the local General Confederation of Italian Industry (in Italian:

Confindustria Alto Milanese) together with a panel of industry representatives of the cluster firms. In 2015, we identified 57 firms working in the footwear industry and focusing on different segments of the value chain: footwear production, accessories development and assembling, and tanning. The data collection took place between March and May 2015. We organized seven focus groups of around 90 min with the firms' representatives; before each focus group, participants completed a questionnaire consisting of a combination of multiple-choice questions on their business and innovation strategy, and a set of questions related to the exchange of knowledge (used for mapping inter-firm networks):

- Technological knowledge: knowledge and expertise for the development of industrial products and processes.
- Market knowledge: knowledge of the characteristics and the preferences of the consumers, as well as the market structure.
- Managerial knowledge: know-how for coordinating and supervising organizational resources and processes.

Previous studies investigated and discussed the existence of multiple inter-firm relationships and their importance for firms' competitiveness (e.g. Meira et al., 2010). In the context of regional clusters, scholars demonstrated that local firms establish several formal and informal relationships: knowledge exchange is a typology of informal relationships, and multiple types (and sources) of knowledge may co-exist in the same cluster (Balland et al., 2016; Capone & Lazzaretti, 2018; Haus-Reve et al., 2019). In this study, we adopt the same approach of Sammarra and Biggiero (2008): technological, market, and managerial knowledge exchange are considered as the main types of knowledge exchange established between firms for supporting innovation processes. Among the multiple-choice questions, we included a question for identifying family firms based on the type of ownership. Network data were collected using a roster-recall method (Scott & Carrington, 2011): we provided the list of all 57 cluster firms to the respondents, and we asked them to indicate with which firm(s) they exchanged a particular type of knowledge or multiple types of knowledge. The completion of the questionnaire was facilitated by the members of the research team.

All representatives of the 39 firms who participated to the focus groups completed the survey, resulting in a response rate of 68%. This response rate is comparable to other studies analyzing knowledge networks in regional clusters (Alberti & Pizzurno, 2015; Boschma & ter Wal, 2007; Broekel & Boschma, 2012; Juhász, 2021), and it is considered acceptable in empirical studies using network data (Cronin, 2016). Moreover, we checked for differences between the two groups of firms (respondents and non-respondents) according to two main firm-level attributes: size and age.[2] Non-respondent firms (18 cases) were slightly younger and smaller than respondents. However, our results can still be considered robust because of the following reasons:

- Smaller firms tend to have less connections because of the lack of resources dedicated to networking.
- Almost half of the non-respondents closed their activities a few years after the data collection period, or even during that period: several Parabiago' firms closed after the 2008–2009 financial crisis, and probably non-respondents were those firms struggling financially and already isolated in the cluster.

3.2 Method

Social Network Analysis (SNA) is extensively used to analyze inter-organizational networks in regional clusters (e.g. Belso-Martínez et al., 2017; Boschma & ter Wal, 2007; Capone & Lazzaretti, 2018; Casanueva et al., 2013; Fritsch & Kauffeld-Monz, 2009; Giuliani & Bell, 2005; Juhász, 2021; Molina-Morales et al., 2015). Different techniques are available for analyzing network data, depending on the data and the hypotheses to test. Exponential Random Graph Models (ERGMs) have become popular to investigate the actor- and structural-level factors associated with the probability of tie formation. ERGMs allow to investigate connections between network actors,

[2] Data about non-respondents were retrieved from official websites and the Bureau van Dijk—AIDA database.

modelling the underlying endogenous mechanisms behind these relationships (Robins et al., 2007; Snijders et al., 2006). Since knowledge networks are unlikely randomly shaped but assumed to follow underlying patterns, ERGMs enable to empirically assess these patterns and verifying if changes in the relational structure depend on actors' characteristics.

The general form of ERGMs is the following (Robins et al., 2007):

$$Pr(Y = y) = (\frac{1}{k})\exp\{\sum_{B} \eta_B g_B(y)\}$$

The probability that the observed network y is identical to the randomly generated network Y is given by an exponential model assuming that η_B is the parameter corresponding to network configuration B and $g_B(y)$ is the network statistic corresponding to configuration B. Assuming homogeneity amongst actor relationships, i.e., all counted network formation instances are equiprobable, Markov dependence allows to identify configurations, and associated parameters, for directed networks.

As dependent variable, ERGMs use the presence of a connection (in our empirical context, knowledge exchange) between actors. This is a dummy variable: if actor i declares to receive knowledge from actor j, then the value in the square matrix on the intersection between row i and column j is equal to 1. In our study, the square matrix is not symmetric, as the knowledge flow has a direction. Moreover, we mapped three different knowledge flow types; therefore, we use three different dependent variables: technological knowledge exchange, market knowledge exchange, and managerial knowledge exchange.

To address our research hypotheses, we use three different variables encompassing differences between family and non-family firms:

- A firm-level attribute variable (*family*) which considers whether a firm is considered a family firm or not—our definition of family firm is based on ownership[3] as a key dimension of familiness (Harms, 2014).
- An edge-level attribute variable (*family_edge*) which considers relationships between family firms only.
- An edge-level attribute variable (*non-family edge*) which considers relationships between non-family firms only.

In our model, we use two different structural-level variables: geometrically weighted edgewise shared partner (*gwesp*) and geometrically weighted dyad-wise shared partners (*gwdsp*). These variables allow to control of structural elements which can influence the development of new relationships. The former is used for mapping triadic closure (Abbasiharofteh & Broekel, 2021), which is the preference for a network's actor to connect with another actor that already has a connection with a third party who is linked to both. Triadic closure is usually associated with trust, and it is considered an important mechanism supporting the evolution of industries and clusters (ter Wal, 2014). *gwdsp* captures effects linked to multi-connectivity strategies: it detects the propensity of firms to connect to each other without direct links (Broekel & Bednarz, 2018).

As edge-level attribute variables, we use proximity measures between cluster firms: geographical distance and cognitive proximity. The idea that geographical distance is a driver of organizational relationships was widely accepted in the past, but more recent work suggests that other measures of proximity are equally important (Boschma, 2005). Therefore, in our models, we control for this aspect. Each measure is defined by a square matrix, where observations refer to the cluster firms. Geographical distance (variable: *geographical*) is determined by the distance between the operative plants of two organizations (Balland, 2012); values in the square matrix express the kilometric distance between plants—considering the shortest road path detected using Google Maps. When different road paths were available in Google Maps, we chose the one with the shortest time travel. To estimate cognitive proximity (Capone & Lazzaretti, 2018; Heringa et al., 2014), we used an index of similarity based on the co-occurrence of similar productive activities between two organizations (variable: *cognitive_jaccard*). This index is the Jaccard binary similarity index.[4] The main idea is that two

[3] In our questionnaire, we asked if the ownership of the company (in terms of equity and property rights) belongs to a family, and the share of equity and property rights owned by the family—and we classified as family firms those who declared that 100% of the above rights are owned by a family, following an approach similar to Samara et al. (2018).

[4] For the estimation process, we used the "Jaccard" function for binary data implemented in Stata17.

firms focusing on the same activities share the same expertise and the same cognitive base (Boschma, 2005). In the questionnaire, we asked to the respondents to indicate what phases of the productive process are carried out in their firm; these phases were mapped with the support of experts from the local General Confederation of Italian Industry. We provided a list of 18 different activities (nine characterizing footwear production and processing, five characterizing accessory production and processing, and four characterizing the tanning process), and once collected all the information, we proceeded with estimating the similarity index.[5] The more the co-occurrence of activities, the higher the similarity index between two firms.

The structural-level variable *edges* is included in the models, to take into account the number of connections which are present in the networks. This configuration controls for the basic assumption that connections between actors exist (Robins et al., 2007) and it must be included in ERGMs because it explains the general likelihood for actors to collaborate (Balland, 2012). Moreover, our ERGMs comprise also other factors (Table 2) that can be associated with the propensity of establishing inter-firm relationships (Belso-Martínez et al., 2017; Broekel & Boschma, 2012; Molina-Morales et al., 2015): *age* (measured in terms of years of activity), *size* (number of employees, a measure of firms' dimension), *export* (tendency to export, a variable accounting for the share of export over the total production), *union* (a dummy variable indicating if a firm is affiliated to the National Association of Footwear Producers—to control for the possibility that firms belonging to this association have a preference to establish connections among each other), and *alliance* (a dummy variable indicating if a firm is engaged in joint ventures or other strategic formal alliances).

For the analysis, we employed the "statnet" suit of packages for R (Handcock et al., 2008).

[5] For example, if Firm A and Firm B are both specialized in Activity 1 and Activity 2 of the tanning process, they have a similarity index equal to 1; if Firm A is specialized in Activity 1 and Activity 2 and Firm B is specialized in Activity 3 and Activity 4, they have a similarity index equal to 0. This index ranges from 0 (no similarity at all) to 1 (complete similarity).

4 Results and discussion

Table 1 shows the descriptive statistics for the variables included in our analysis. Firms' size is heterogenous, since there are a few large companies with more than 200 employees and several small and micro companies. Overall, Parabiago's firms have a high tendency to export towards other countries (on average, they export 45% of their total production); this is consistent with the historical background of Parabiago and many other Italian clusters, since Italian cluster firms are often searching for new markets (Dei Ottati, 1994). Around 31% of Parabiago's firms are affiliated to the National Association of Footwear Producers; moreover, one-third of all cluster firms have an active formal partnership with other firms inside or outside the cluster. This indicates that a large portion of firms have experience of networking. Interestingly, family firms are not concentrating on exporting abroad, as indicated by the negative correlation between "export" and "family" (Table 2), while those firms affiliated to the National Association of Footwear Producers can be considered exporters. Geographical distance and cognitive proximity are negatively correlated (Table 3): firms focusing on the same productive activities were probably established closer to each other, as discussed by Becattini (1987) in his study on the evolution of Italian industrial districts.

Figures 1, 2 and 3 represent the three knowledge networks mapped in Parabiago; all graphs have been created using NetDraw. On average, firms have around four connections (average degree) in the technological knowledge network, two in the market knowledge network, and one in the managerial knowledge network. The density of the networks, i.e., the ratio between the number of observed ties on the total number of possible ties (Prell, 2012), is higher in the technological knowledge network. Moreover, the technological knowledge network has the lower number of isolates (firms with no connections) (Table 4). The exchange of technological knowledge seems dominant in Parabiago; this uneven distribution of knowledge—and the prevalence of technological knowledge over others—is rather expected, since it was observed in other studies investigating knowledge exchange patterns in regional clusters (Boschma & ter Wal, 2007; Sammarra & Biggiero, 2008).

Table 1 Descriptive statistics

Variable	Description	Type	Mean	Std. dev	Min	Max
Age	Years of activity	Continuous	38.92	22.81	1	96
Size	Number of employees	Continuous	50.13	71.16	1	270
Export	Share of export	Percentage (0–100%) over the total production	44.95	41.32	0	100
Union	Affiliation to the National Association of Footwear Producers	Dummy variable (0 = no; 1 = yes)	0.31	0.47	0	1
Alliance	Engagement in joint ventures or other strategic (formal) alliances	Dummy variable (0 = no; 1 = yes)	0.33	0.48	0	1
Family	Family organization	Dummy (0 = no; 1 = yes)	0.69	0.47	0	1
Geographical	Distance between firms (km)	Continuous	9.28	8.29	0.10	44.40
Cognitive_jaccard	Similarity index	Continuous	0.65	0.20	0.18	1

Table 2 Correlation analysis: firm-level attributes

	Age	Size	Export	Union	Alliance	Family
Age	1.00					
Size	0.14	1.00				
Export	0.14	0.13	1.00			
Union	0.05	0.45	0.55	1.00		
Alliance	0.14	0.15	−0.01	0.24	1.00	
Family	0.22	0.02	−0.44	−0.24	0.15	1.00

Table 3 QAP correlation: edge-level attributes (geographical and cognitive proximity)

	Geographical	Cognitive_jaccard
Geographical	1.00	
Cognitive_jaccard	-0.49	1.00

The peculiar structure of the technological knowledge network and the similarities between the other two knowledge networks are confirmed by the results of the Quadratic Assignment Procedure-QAP correlation (Dekker et al., 2007; Scott & Carrington, 2011). There is a strong positive correlation (0.65) between the market and managerial knowledge networks; they exhibit a very similar relational structure, while their level of similarity with the technological knowledge network is much lower.

The results of the ERGMs are presented in Table 5. Since coefficients reflect the change in the (log-odds) likelihood of a tie for a unit change in the predictors, they must be translated into a probability using the exponential function. ERGMs 1a, 2a, and 3a estimate the effects of a baseline model which controls for firm-level attributes and estimates the association between tie formation and the probability of being a family firm or not (variable *family*). Models 1b, 2b, and 3b introduce the edge-level attributes, including the proximity measures (geographical and cognitive) and the variable *family_edge*, which estimates the association between tie formation and the presence of relationships between family firms only. Models 1c, 2c, and 3c are built on the same premises but instead of estimating the effect for family firms only, they look at non-family firms: the variable *non-family edge* provides information about the association between tie formation and non-family firm relationships. The sensitivity analysis (following Dekker et al. (2007) and Hunter et al. (2008); see the Appendix) supports the robustness of our results. The values for

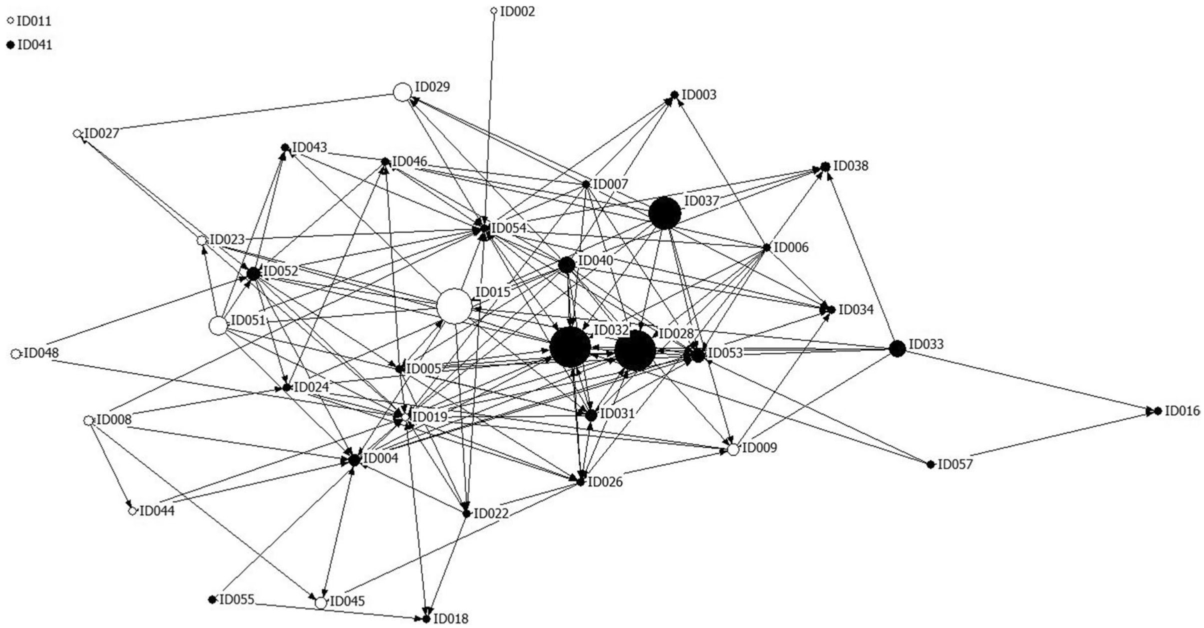

Fig. 1 Technological knowledge network. Legend: nodes' size is proportional to the number of employees. Black node = family firm; white node = non-family firm

the Akaike Information Criteria (AIC) and Bayesian Information Criterion (BIC) (two means of scoring a model based on its log-likelihood and complexity) decrease when edge-level attributes are added to the models. We assessed the goodness of fit of the models by comparing the observed networks with a

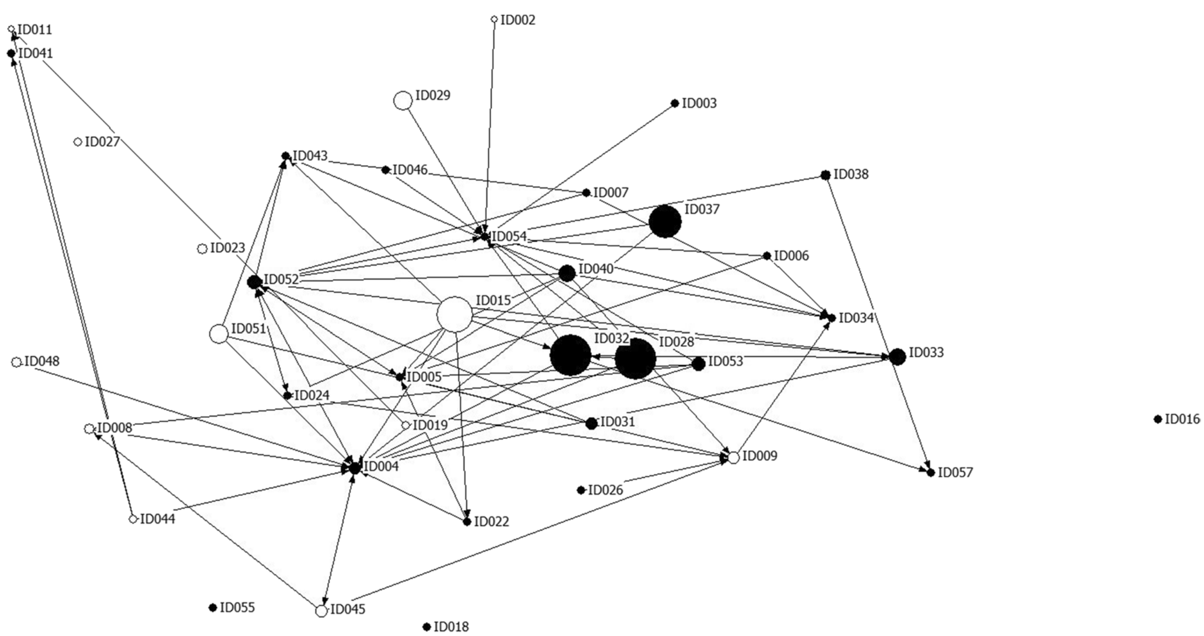

Fig. 2 Market knowledge network. Legend: nodes' size is proportional to the number of employees. Black node = family firm; white node = non-family firm

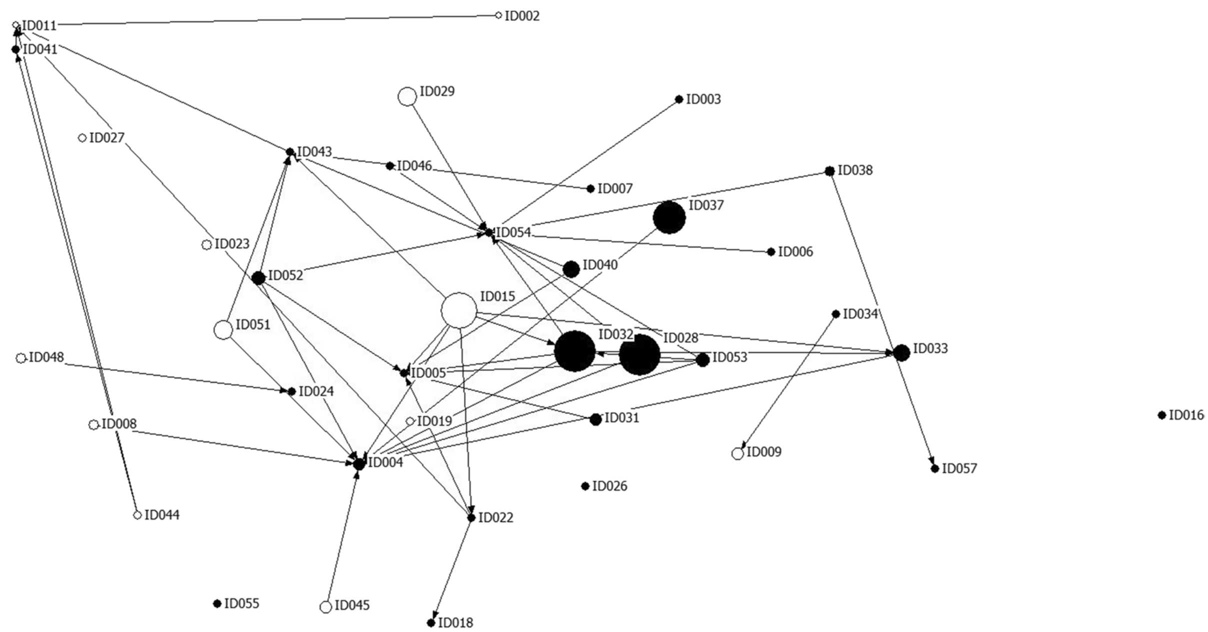

Fig. 3 Managerial knowledge network. Legend: nodes' size is proportional to the number of employees. Black node = family firm; white node = non-family firm

Table 4 Networks' statistics

Knowledge network	Nodes	Number of ties	Average degree	Density	Isolates	QAP correlation	
Technological	39	165	4.23	0.11	2		
Market	39	68	1.77	0.05	5	0.34	
Managerial	39	46	1.18	0.03	6	0.30	0.65

set of simulated networks (Hunter et al., 2008).All the parameters related to the firm- and edge-level attributes have acceptable *p*-values (mostly included between 0.80 and 1.00); moreover, the models perform well for the (in- and out-) degree distribution and the geodesics distribution; moreover, they perform really well for the shared partner distribution.

At the dyadic level, we can see that the coefficients for *geographical* and *cognitive_jaccard* are always negative. These results are partially aligned with the literature. Firms that are more geographically distant tend to establish fewer connections (e.g. Balland et al., 2016), and this is confirmed by our results; however, previous studies found that cognitive proximity is positively associated with the exchange of tacit knowledge (e.g. Capone & Lazzaretti, 2018), while in our study is not. We assume that the presence of firms operating in different segments of the supply chain enables local actors to search for partners which can provide feedback on different aspects of the production process. At the structural level, *gwesp* is positive and statistically significant in all networks, while *gwdsp* is always negative and statistically significant. This means that social embeddedness, or the presence of triads in the network, is a powerful element explaining the existence of inter-firm knowledge exchange (Abbasiharofteh & Broekel, 2021; Juhász, 2021); on the other hand, firms that are not able to develop different network strategies for connecting with other firms might be penalized. This result, while counterintuitive, has been previously observed by Broekel and Bednarz (2018), who argued that firms might prefer to maximize knowledge diffusion by increasing link dependencies, rather than increasing it.

Table 5 ERGMs results

	Technological			Market			Managerial		
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Edges	−2.231 (0.391) ***	−0.761 (0.398) *	−0.663 (0.393) *	−4.249 (0.477) ***	−3.083 (0.481) ***	−2.761 (0.473) ***	−4.340 (0.702) ***	−3.005 (0.591) ***	−2.670 (0.587) ***
Age	−0.006 (0.003) *	−0.009 (0.004) **	−0.005 (0.003)	−0.002 (0.004)	−0.003 (0.004)	−0.0001 (0.0038)	0.0005 (0.0055)	0.0003 (0.0053)	0.002 (0.005)
Size	0.005 (0.001) ***	0.005 (0.001) ***	0.005 (0.001) ***	0.002 (0.001) *	0.002 (0.001) *	0.002 (0.001) *	0.003 (0.002) *	0.003 (0.002) **	0.003 (0.002) **
Export	−0.001 (0.002)	−0.001 (0.002)	−0.003 (0.002)	0.006 (0.003) **	0.008 (0.003) **	0.005 (0.003) *	0.005 (0.004)	0.005 (0.004)	0.003 (0.004)
Union	−0.154 (0.211)	0.013 (0.231)	0.009 (0.229)	−0.382 (0.258)	−0.305 (0.290)	−0.301 (0.279)	−0.400 (0.375)	−0.382 (0.379)	−0.389 (0.378)
Alliance	0.706 (0.159) ***	0.841 (0.164) ***	0.875 (0.165) ***	0.220 (0.176)	0.288 (0.190)	0.340 (0.185) *	0.463 (0.250) *	0.523 (0.248) **	0.560 (0.253) **
gwesp (fixed 0.25)	0.479 (0.174) ***	0.360 (0.165) **	0.418 (0.163) **	1.443 (0.217) ***	1.365 (0.221) ***	1.448 (0.221) ***	2.292 (0.472) ***	2.254 (0.405) ***	2.270 (0.444) ***
gwdsp (fixed 1.2)	−0.202 (0.023) ***	−0.214 (0.022) ***	−0.214 (0.023) ***	−0.276 (0.075) ***	−0.295 (0.075) ***	−0.277 (0.083) ***	−1.148 (0.264) ***	−1.146 (0.233) ***	−1.144 (0.265) ***
Family	0.408 (0.177) **			0.582 (0.226) **			0.572 (0.312) *		
Geographical		−0.059 (0.013) ***	−0.054 (0.014) ***		−0.043 (0.017) **	−0.042 (0.018) **		−0.061 (0.023) ***	−0.061 (0.025) **
Cognitive_jaccard		−2.091 (0.398) ***	−2.205 (0.404) ***		−1.641 (0.555) ***	−1.726 (0.586) ***		−1.253 (0.611) **	−1.259 (0.625) **
Family_edge		0.614 (0.213) ***			0.749 (0.273) ***			0.602 (0.331) *	
Non-family edge			0.258 (0.360)			−0.191 (0.518)			−0.843 (0.788)
AIC	935.5	899.2	907.0	520.9	512.4	519.4	363.3	360.3	361.8
BIC	983.2	957.5	965.3	568.6	570.8	577.7	411.0	418.6	420.1

Legend: *Result significant at 90%, **Result significant at 95%, ***Result significant at 99%

Our results suggest that when considering the propensity to exchange knowledge, being a family firm is a driver for collaboration: *family* is always positive and statistically significant for all the types of knowledge exchanged. This suggests that family firms are more prone to fostering knowledge exchange within regional clusters, confirming Hypothesis 1. Second, family firms are prone to establish knowledge exchanges with other family firms: this is confirmed by the positive and statistically significant results for *family_edge* in all three models (1b, 2b, and 3b), and it confirms Hypothesis 2. This suggests that family firms prefer other family firms for exchanging knowledge, perhaps because they recognize some similarities in their strategic approach and because they do not consider non-family firms as trustworthy as other family firms. The magnitude for the *family_edge* coefficient in the managerial knowledge network is the lowest in all models. Family firms may want to search for managerial knowledge also outside the cluster, perhaps with organizations that cannot be found in Parabiago. According to Duong et al. (2022), the association between innovation output and knowledge acquisition from universities and research institutes is particularly strong in family firms. Since universities and research institutes are providers of business- and managerial-related knowledge and advice, it is reasonable to assume that family firms search for managerial knowledge from specialised actors outside the cluster.

Finally, *non-family edge* is never statistically significant and does not have a clear coefficient: it is positive for the technological knowledge exchange network, but negative for the other two networks. This result suggests that non-family firms do not have a clear preference for establishing connections with other non-family firms, and thus, their network strategies are completely different from family firms. Hence, we can talk about homophilous approaches to networking for family firms only, not for non-family firms. These findings can be considered in the context of recent evidence on innovation performance contrasting family and non-family firms, suggesting that firm type plays a distinct role in moderating the relationship between the use of knowledge obtained from external sources and innovation performance. When looking at innovation collaborations, family firms tend to have a lower degree of formalization compared to non-family firms (Duong et al., 2022), and this might have an impact on the way they interact with other market-based actors—which reflects in their networking strategy when deciding to acquire different types of knowledge.

5 Conclusions

In spite of an extensive literature contrasting family and non-family firms, our understanding of the role and characteristics of family firms' inter-organizational knowledge networks in the context of regional clusters is still limited. Based on the analysis of network data from one of Italy's most important footwear clusters, our findings suggest not only that family firms have a key role to play in the exchange of different knowledge types (technological, market, and managerial knowledge), but also that family firms are always more prone in fostering knowledge exchange among themselves relatively to non-family firms, suggesting that being a family firm relates to knowledge-exchange idiosyncrasies. These findings suggest that the nature of ownership—and thus the key difference between family and non-family firms—is driving knowledge exchange differences. The results on the distinctiveness of family and non-family firms with regard to knowledge-sharing strategies can be compared to other works that have equally found distinct patterns across family and non-family firms relating to knowledge exchange: factors explaining such distinct patterns include distinct business practices and mechanisms (Chang et al., 2022; Clauß et al., 2022), differences in external knowledge sourcing (Duong et al., 2022), or path dependence (Lorenzo et al., 2022).

Our work provides empirical evidence supporting the idea that endogenous network effects can explain cluster evolution. While we cannot specifically talk about network dynamics (see the below limitations of our study), we can say that transitivity, proximity, and homophily are key elements to be considered when investigating cluster relationships based on knowledge exchange (as discussed by Abbasiharofteh, 2020). Moreover, we contribute to this theoretical discussion by adding a novel element of analysis: the distinction between family ad non-family firms. Firms are intrinsically different, and their networking strategies depend on their intra-organizational structure. Cluster firms do not follow the same strategic approaches: strategies are based on different needs and objectives, and this is particularly evident when it comes to family firms (Zellweger et al., 2019). Based on our findings, we assume that clusters would evolve differently without family firms. These firms are shaping the knowledge exchange network in Parabiago, which means that their presence is key for the survival of the cluster—seen as a traditional regional cluster as described by Marshall (1920) and Becattini (1987). Differently from non-family firms, family firms' networking approach is based on homophily; if confirmed also in other contexts, this would mean that homophily can be considered an important network effect but only for certain cluster actors. Future (theoretical and empirical) studies should consider these aspects when examining cluster network dynamics.

In terms of managerial and policy implications, our findings suggest that the distinct differences between family and non-family firms when it comes to knowledge exchange strategies require distinct managerial and policy tools as part of effective and targeted efforts for cluster growth. This insight may be valuable to both cluster managers and managers of the very family firms participating in clusters. Regarding the former, it is still striking that in the European Union family firms continue to be omitted from public policy beyond direct action related to tax benefits or advice about ownership and management succession (see Basco & Bartkevičiūtė, 2016). Hence in terms of policy implications, our results support the work of Basco and Bartkevičiūtė (2016): any public policy intervention should consider the regional familiness characteristics of the regional productive structure. Regarding the implications for family firm managers, our results suggest that a managerial focus on knowledge exchange between cluster-based family firms may lead to the development of structured networks which are likely to impact on innovation premia and other knowledge-sharing benefits that may outweigh potential costs. Nevertheless, potential benefits such as increased resilience from being able to connect across different firm types for a more inclusive ecosystem-like knowledge-sharing approach in clusters must not be overlooked: if intra-cluster network dynamics exist, it is necessary to comprehend what incentives can be developed for supporting (or adjusting) these dynamics, and if the involvement of external actors (such as venture capital firms, universities and research institutes) acting as brokers can favor the establishment of durable partnerships leading to formalized collaborations and performance benefits. The idea that establishing such relationships with external partners can boost innovation outcomes for family firms—and therefore producing benefits for the cluster and the regional ecosystems as well—was documented in previous studies (e.g. Muñoz-Bullón et al., 2020; Su & Daspit, 2021).

Finally, as a further policy implication, our key finding that family firms have a higher propensity to establish connections suggests that cluster management needs to balance support for distinct business types and support for integrative cluster performance. Hence, it is necessary to support the creation of a shared cluster culture capable of pursuing a cluster long-term vision, while allowing for the pursuit of different knowledge-sharing patterns by firm type. This balanced and differential approach might be required especially at different stages of cluster growth or even for different family-firm sizes when issues of trust have varying importance (Chang et al., 2022). This resonates also with calls for a different model of industrial policy for regional clusters (Hudec et al., 2021; Schmitz & Musyck, 2016): entrepreneurs of all ownership status need to interact with local stakeholders to develop a common cluster strategy; otherwise, their individualism may contribute to impede local relationships. From a theoretical point of view, our work contributes to the wider academic debate on inter-firm networks in at least two ways. First, our findings on family firms' relationships with regard to knowledge transfer could be read in the context of the path-dependent capabilities influencing innovation in family firms (Lorenzo et al., 2022), thereby highlighting further the complexity underlying the nexus of knowledge exchange, innovation in family-firms and their networks (Chirico et al., 2022). Second, we contribute to the wider debate on inter-firm networks and knowledge transfer, by highlighting that family firm–based networks can be usefully understood and connected within the literatures on social capital and entrepreneurship: not only by recognizing that entrepreneurs and entrepreneurship are socially situated (Herrero et al., 2021), but also considering the uniqueness of family firms in the development of organizational social capital and inter-firm networks (Yates et al., 2022).

Our paper faces some limitations, which need to be addressed in further research. First, the sector-specific nature of our database means that the transferability of our results needs to be explored further. In this context, the very definitions of technological, market, and managerial knowledge exchange are naturally context- and thus sector-specific and therefore need to be explored in other contexts for robustness. Second, as a function of the methods and data employed, we were not able to investigate the nature of the relationship in a dynamic context, and how this affects knowledge exchange (see Hermans, 2021). Third, in contrast to other studies (e.g. Pittino et al., 2021; Zahra et al., 2007), we did not control for the actual level of family (e.g., multi-generational) involvement in governance and managerial knowledge exchange, leading to the here unexplored issue of path dependence in family firms (Lorenzo et al., 2022). Keeping these limitations in mind, future research may try to assess the robustness of our findings, by assessing family and non-family firm networks in footwear clusters in other countries or assess inter-firm network issues in other sectors and clusters that hold structural similarities (such as creative clusters). Furthermore, a longitudinal research perspective with performance measures could also contribute to the debate about costs and benefits of familiness.

Data Availability Restrictions apply to the availability of the data used in this study. The data are, however, available from the authors upon reasonable request.

References

Abbasiharofteh, M. (2020). Endogenous effects and cluster transition: A conceptual framework for cluster policy. *European Planning Studies, 28*(12), 2508–2531. https://doi.org/10.1080/09654313.2020.1724266

Abbasiharofteh, M., & Broekel, T. (2021). Still in the shadow of the wall? The case of the Berlin biotechnology cluster. *Environment and Planning A, 53*(1), 73–94. https://doi.org/10.1177/0308518X20933904

Alberti, F. G., & Pizzurno, E. (2015). Knowledge exchanges in innovation networks: Evidences from an Italian aerospace cluster. *Competitiveness Review, 25*(3), 258–287. https://doi.org/10.1108/CR-01-2015-0004

Alberti, F. G., & Pizzurno, E. (2017). Oops, I did it again! Knowledge leaks in open innovation networks with start-ups. *European Journal of Innovation Management, 20*(1), 50–79. https://doi.org/10.1108/EJIM-11-2015-0116

Ardito, L., Petruzzelli, A. M., Pascucci, F., & Peruffo, E. (2019). Inter-firm R&D collaborations and green innovation value: The role of family firms' involvement and the moderating effects of proximity dimensions. *Business Strategy and the Environment, 28*, 185–197. https://doi.org/10.1002/bse.2248

Arregle, J. L., Hitt, M. A., Sirmon, D. G., & Very, P. (2007). The development of organizational social capital: Attributes of family firms. *Journal of Management Studies, 44*(1), 73–95. https://doi.org/10.1111/j.1467-6486.2007.00665.x

Balland, P.-A. (2012). Proximity and the evolution of collaboration networks: Evidence from research and development projects within the Global Navigation Satellite System (GNSS) Industry. *Regional Studies, 46*(6), 741–756. https://doi.org/10.1080/00343404.2010.529121

Balland, P.-A., Belso-Martínez, J. A., & Morrison, A. (2016). The dynamics of technical and business knowledge networks in industrial clusters: Embeddedness, status, or proximity? *Economic Geography, 92*(1), 35–60. https://doi.org/10.1080/00130095.2015.1094370

Basco, R., & Bartkevičiūtė, I. (2016). Is there any room for family business into European Union 2020 Strategy? Family business and regional public policy. *Local Economy, 31*(6), 709–732. https://doi.org/10.1177/0269094216664485

Baù, M., Chirico, F., Pittino, D., Backman, M., & Klaesson, J. (2019). Roots to grow: Family firms and local embeddedness in rural and urban contexts. *Entrepreneurship Theory and Practice, 43*(2), 360–385. https://doi.org/10.1177/1042258718796089

Becattini, G. (1987). *Mercato e forze locali. Il distretto industriale*. Il Mulino.

Belso-Martínez, J. A., Expósito-Langa, M., & Tomás-Miquel, J.-V. (2016). Knowledge network dynamics in clusters: Past performance and absorptive capacity. *Baltic Journal of Management, 11*(3), 310–327. https://doi.org/10.1108/BJM-02-2015-0044

Belso-Martínez, J. A., Mas-Tur, A., & Roig-Tierno, N. (2017). Synergistic effects and the co-existence of networks in clusters. *Entrepreneurship & Regional Development, 29*(1–2), 137–154. https://doi.org/10.1080/08985626.2016.1255429

Bichler, B. F., Kallmuenzer, A., Peters, M., Petry, T., & Clauss, T. (2022). Regional entrepreneurial ecosystems: How family firm embeddedness triggers ecosystem development. *Review of Managerial Science, 16*(1), 15–44. https://doi.org/10.1007/s11846-020-00434-9

Bjuggren, P.-O., & Sund, L.-G. (2002). A transaction cost rationale for transition of the firm within the family.

Small Business Economics, 19(2), 123–133. https://doi.org/10.1023/A:1016289106477
Block, J. H., & Spiegel, F. (2013). Family firm density and regional innovation output: An exploratory analysis. *Journal of Family Business Strategy, 4*, 270–280. https://doi.org/10.1016/j.jfbs.2013.10.003
Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies, 39*(1), 61–74. https://doi.org/10.1080/0034340052000320887
Boschma, R. A., & ter Wal, A. L. J. (2007). Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the South of Italy. *Industry and Innovation, 14*(2), 177–199. https://doi.org/10.1080/13662710701253441
Broekel, T., & Bednarz, M. (2018). Disentangling link formation and dissolution in spatial networks: An Application of a Two-Mode STERGM to a Project-Based R&D Network in the German Biotechnology Industry. *Networks and Spatial Economics, 18*(3), 677–704. https://doi.org/10.1007/s11067-018-9430-1
Broekel, T., & Boschma, R. (2012). Knowledge networks in the Dutch Aviation Industry: The proximity paradox. *Journal of Economic Geography, 12*(2), 409–433. https://doi.org/10.1093/jeg/lbr010
Cainelli, G., & Zoboli, R. (2004). *The evolution of industrial districts*. Physica-Verlag.
Capone, F., & Lazzaretti, L. (2018). The different roles of proximity in multiple informal network relationships: Evidence from the cluster of high technology applied to cultural goods in Tuscany. *Industry and Innovation, 25*(9), 897–917. https://doi.org/10.1080/13662716.2018.1442713
Casanueva, C., Castro, I., & Galán, J. L. (2013). Informational networks and innovation in mature industrial clusters. *Journal of Business Research, 66*(5), 603–613. https://doi.org/10.1016/j.jbusres.2012.02.043
Casprini, E., De Massis, A., Di Minin, A., Frattini, F., & Piccaluga, A. (2017). How family firms execute open innovation strategies: The Loccioni case. *Journal of Knowledge Management, 21*(6), 1459–1485. https://doi.org/10.1108/JKM-11-2016-0515
Chang, E. P. C., Zare, S., & Ramadani, V. (2022). How a larger family business is different from a non-family one? *Journal of Business Research, 139*, 292–302. https://doi.org/10.1016/j.jbusres.2021.09.060
Chirico, F., Ireland, R. D., Pittino, D., & Sanchez-Famoso, V. (2022). Radical innovation in (multi) family owned firms. *Journal of Business Venturing, 37*(3), 106194. https://doi.org/10.1016/j.jbusvent.2022.106194
Clauß, T., Kraus, S., & Jones, P. (2022). Sustainability in family business: Mechanisms, technologies and business models for achieving economic prosperity, environmental quality and social equity. *Technological Forecasting and Social Change, 176*, 121450. https://doi.org/10.1016/j.techfore.2021.121450
Clinton, E., McAdam, M., & Gamble, J. R. (2018). Transgenerational entrepreneurial family firms: An examination of the business model construct. *Journal of Business Research, 90*, 269–285. https://doi.org/10.1016/j.jbusres.2018.04.032
Coli, A., & Rose, M. B. (1999). Families and firms: The culture and evolution of family firms in Britain and Italy in the nineteenth and twentieth centuries. *Scandinavian Economic History Review, 47*(1), 24–47. https://doi.org/10.1080/03585522.1999.10419803
Cooke, P. (2002). Regional innovation systems: General findings and some new evidence from biotechnology clusters. *The Journal of Technology Transfer, 27*(1), 133–145. https://doi.org/10.1023/A:1013160923450
Cronin, B. (2016). Social network analysis. In F. S. Lee & B. Cronin (Eds.), *Handbook of Research Methods and Applications in Heterodox Economics* (pp. 237–252). Edward Elgar Publishing.
De Massis, A., Frattini, F., & Lichtenthaler, U. (2013). Research on technological innovation in family firms: Present debates and future Directions. *Family Business Review, 26*, 10–31. https://doi.org/10.1177/0894486512466258
Dei Ottati, G. (1994). Trust, interlinking transactions and credit in the industrial district. *Cambridge Journal of Economics, 18*(6), 529–546. https://doi.org/10.1093/oxfordjournals.cje.a035289
Dekker, D., Krackhardt, D., & Snijders, T. A. B. (2007). Sensitivity of MRQAP Tests to collinearity and autocorrelation conditions. *Psychometrika, 72*, 563–581. https://doi.org/10.1007/s11336-007-9016-1
Duong, P. A. N., Voordeckers, W., Huybrechts, J., & Lambrechts, F. (2022). On external knowledge sources and innovation performance: Family versus non-family firms. *Technovation, 114*, 102448. https://doi.org/10.1016/j.technovation.2021.102448
Easterby-Smith, M., Lyles, M. A., & Tsang, E. W. (2008). Inter-organizational knowledge transfer: Current themes and future prospects. *Journal of Management Studies, 45*(4), 677–690. https://doi.org/10.1111/j.1467-6486.2008.00773.x
Feranita, F., Kotlar, J., & De Massis, A. (2017). Collaborative innovation in family firms: Past research, current debates and agenda for future research. *Journal of Family Business Strategy, 8*, 137–156. https://doi.org/10.1016/j.jfbs.2017.07.001
Ferretti, M., Guerini, M., Panetti, E., & Parmentola, A. (2021). The partner next door? The effect of micro-geographical proximity on intra-cluster inter-organizational relationships. *Technovation*, 102390. https://doi.org/10.1016/j.technovation.2021.102390
Fritsch, M., & Kauffeld-Monz, M. (2009). The impact of network structure on knowledge transfer: An application of social network analysis in the context of regional innovation networks. *Annals of Regional Science, 44*(1), 21–38. https://doi.org/10.1007/s00168-008-0245-8
Giuliani, E. (2007). The selective nature of knowledge networks in clusters: Evidence from the wine industry. *Journal of Economic Geography, 7*(2), 139–168. https://doi.org/10.1093/jeg/lbl014
Giuliani, E., & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. *Research Policy, 34*, 47–68. https://doi.org/10.1016/j.respol.2004.10.008
Giuliani E. (2010). Network dynamics in regional clusters: A new perspective from an emerging economy. Industry Studies Association Working Papers, WP-2010–09, from http://isapapers.pitt.edu/187/. Accessed 15 Dec 2021

González, C., & González-Galindo, A. (2022). The institutional context as a source of heterogeneity in family firm internationalization strategies: A comparison between US and emerging market family firms. *International Business Review*, 101972. https://doi.org/10.1016/j.ibusrev.2021.101972

Gulati, J., & Gargiulo, M. (1999). Where do interorganizational networks come from? *American Journal of Sociology, 104*(5), 1439–1493. https://doi.org/10.1086/210179

Gurrieri, A. R. (2008). Knowledge network dissemination in a family-firm sector. *The Journal of Socio-Economics, 37*(6), 2380–2389. https://doi.org/10.1016/j.socec.2008.04.005

Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., & Morris, M. (2008). Statnet: Sofware tools for the representation, visualization, analysis and simulation of network data. *Journal of Statistical Software*, *24*(1), 1548–7660. https://doi.org/10.18637/jss.v024.i01

Harms, H. (2014). Review of family business definitions: Cluster approach and implications of heterogeneous application for family business research. *International Journal of Financial Studies, 2*(3), 280–314. https://doi.org/10.3390/ijfs2030280

Haus-Reve, S., Fitjar, R. D., & Rodríguez-Pose, A. (2019). Does combining different types of collaboration always benefit firms? Collaboration, complementarity and product innovation in Norway. *Research Policy, 48*(6), 1476–1486. https://doi.org/10.1016/j.respol.2019.02.008

Heringa, P. W., Horlings, E., van der Zouwen, M., van den Besselaar, P., & van Vierssen, W. (2014). How do dimensions of proximity relate to the outcomes of collaboration? *Economics of Innovation and New Technology, 23*, 689–716. https://doi.org/10.1080/10438599.2014.882139

Hermans, F. (2021). The contribution of statistical network models to the study of clusters and their evolution. *Papers in Regional Science, 100*(2), 379–403. https://doi.org/10.1111/pirs.12579

Herrero, I., Hughes, M., & Larrañeta, B. (2021). Is blood thicker than water? Exploring the impact of family firms' familial social relations with other firms within their industries. *Journal of Family Business Strategy*, 100471. https://doi.org/10.1016/j.jfbs.2021.100471

Hudec, O., Gazda, V., Zoričák, M., & Horváth, D. (2021). Industrial districts as the outcome of self-organisation in time and space. In A. Reggiani, L. A. Schintler, D. Czamanski, & R. Patuelli (Eds.), *Handbook on Entropy, Complexity and Spatial Dynamics* (pp. 342–362). Edward Elgar Publishing.

Humphrey, J., & Schmitz, H. (1996). The Triple C approach to local industrial policy. *World Development, 24*(12), 1859–1877. https://doi.org/10.1016/S0305-750X(96)00083-6

Hunter, D., Goodreau, S., & Handcock, M. (2008). Goodness of fit of social network models. *Journal of the American Statistical Association, 103*(481), 248–258. https://doi.org/10.1198/016214507000000446

Iammarino, S., & McCann, P. (2006). The structure and evolution of industrial clusters: Transactions, technology and knowledge spillovers. *Research Policy, 35*(7), 1018–1036. https://doi.org/10.1016/j.respol.2006.05.004

Inkpen, A. C., & Tsang, E. W. K. (2005). Social capital networks, and knowledge transfer. *Academy of Management Review, 30*(1), 146–165. https://doi.org/10.5465/amr.2005.15281445

Juhász, S. (2021). Spinoffs and tie formation in cluster knowledge networks. *Small Business Economics, 56*, 1385–1404. https://doi.org/10.1007/s11187-019-00235-9

Juhász, S., & Lengyel, B. (2018). Creation and persistence of ties in cluster knowledge networks. *Journal of Economic Geography, 18*(6), 1203–1226. https://doi.org/10.1093/jeg/lbx039

Lambrechts, F., Voordeckers, W., Roijakkers, N., & Vanhaverbeke, W. (2017). Exploring open innovation in entrepreneurial private family firms in low- and medium-technology industries. *Organizational Dynamics, 46*(4), 244–261. https://doi.org/10.1016/j.orgdyn.2017.05.001

Lattuch, F. (2019). Family firm innovation strategy: Contradictions and tradition. *Journal of Business Strategy, 40*(3), 36–42. https://doi.org/10.1108/JBS-03-2018-0046

Leppäaho, T., Chetty, S., & Dimitratos, P. (2018). Network embeddedness in the internationalization of biotechnology entrepreneurs. *Entrepreneurship & Regional Development, 30*(5–6), 562–584. https://doi.org/10.1080/08985626.2017.1408697

Lorenzo, D., Núñez-Cacho, P., Akhter, N., & Chirico, F. (2022). Why are some family firms not innovative? Innovation Barriers and Path Dependence in Family Firms. *Scandinavian Journal of Management, 38*(1), 101182. https://doi.org/10.1016/j.scaman.2021.101182

Lude, M., & Prügl, R. (2019). Risky decisions and the family firm bias: An experimental study based on prospect theory. *Entrepreneurship Theory and Practice, 43*(2), 386–408. https://doi.org/10.1177/1042258718796078

Mariotti, S., Marzano, R., & Piscitello, L. (2021). The role of family firms' generational heterogeneity in the entry mode choice in foreign markets. *Journal of Business Research, 132*, 800–812. https://doi.org/10.1016/j.jbusres.2020.10.064

Marra, A., Carlei, V., & Baldassari, C. (2020). Exploring networks of proximity for partner selection, firms' collaboration and knowledge exchange. The case of clean-tech industry. *Business Strategy and the Environment*, *29*(3), 1034–1044. https://doi.org/10.1002/bse.2415

Marshall, A. (1920). *Principles of Economics*. MacMillan.

Mathews, M., & Stokes, P. (2013). The creation of trust: The interplay of rationality, institutions and exchange. *Entrepreneurship & Regional Development, 25*(9–10), 845–866. https://doi.org/10.1080/08985626.2013.845695

Meira, J., Kartalis, N. D., Tsamenyi, M., & Cullen, J. (2010). Management controls and inter-firm relationships: A review. *Journal of Accounting & Organizational Change, 6*(1), 149–169. https://doi.org/10.1108/18325911011025731

Molina-Morales, F. X., Belso-Martínez, J. A., Más-Verdú, F., & Martínez-Cháfer, L. (2015). Formation and dissolution of inter-firm linkages in lengthy and stable networks in clusters. *Journal of Business Research, 68*, 1557–1562. https://doi.org/10.1016/j.jbusres.2015.01.051

Muñoz-Bullón, F., Sanchez-Bueno, M. J., & De Massis, A. (2020). Combining internal and external R&D: The effects on innovation performance in family and nonfamily firms. *Entrepreneurship Theory and Practice, 44*(5), 996–1031.

Oliver, A. L., & Ebers, M. (1998). Networking network studies: An analysis of conceptual configurations in the study of inter-organizational relationships. *Organization Studies, 19*(4), 549–583. https://doi.org/10.1177/017084069801900402

Prell, C. (2012). *Social network analysis: History, theory, and methodology*. SAGE.

Pittino, D., Visintin, F., Minichilli, A., & Compagno, C. (2021). Family involvement in governance and firm performance in industrial districts. The moderating role of the industry's technological paradigm. *Entrepreneurship & Regional Development*, *33*(7–8), 514–531. https://doi.org/10.1080/08985626.2021.1925848

Podolny, J. M., & Page, K. L. (1998). Network forms of organization. *Annual Review of Sociology, 24*, 57–76. https://doi.org/10.1146/annurev.soc.24.1.57

Pucci, T., Brumana, M., Minola, T., & Zanni, L. (2020). Social capital and innovation in a life science cluster: The role of proximity and family involvement. *The Journal of Technology Transfer, 45*(1), 205–227. https://doi.org/10.1007/s10961-017-9591-y

Ricotta, F., & Basco, R. (2021). Family firms in European regions: The role of regional institutions. *Entrepreneurship & Regional Development, 33*(7–8), 532–554. https://doi.org/10.1080/08985626.2021.1925849

Robins, G., Pattison, P., Kalish, Y., & Lusher, D. (2007). An introduction to exponential random graph (p*) models for social networks. *Social Networks, 29*(2), 173–191. https://doi.org/10.1016/j.socnet.2006.08.002

Samara, G., Jamali, D., Sierra, V., & Parada, M. J. (2018). Who are the best performers? The environmental social performance of family firms. *Journal of Family Business Strategy, 9*(1), 33–43. https://doi.org/10.1016/j.jfbs.2017.11.004

Sammarra, A., & Biggiero, L. (2008). Heterogeneity and specificity of inter-firm knowledge flows in innovation networks. *Journal of Management Studies, 45*(4), 800–829. https://doi.org/10.1111/j.1467-6486.2008.00770.x

Schmitz, H., & Musyck, B. (2016). Industrial districts in Europe: Policy lessons for developing countries? In T. Hashino & K. Otsuka (Eds.), *Industrial Districts in History and the Developing World* (pp. 117–151). Springer.

Sciascia, S., Mazzola, P., & Chirico, F. (2013). Generational involvement in the top management team of family firms: Exploring nonlinear effects on entrepreneurial orientation. *Entrepreneurship: Theory and Practice*, *37*(1), 69–85. https://doi.org/10.1111/j.1540-6520.2012.00528.x

Scott, J., & Carrington, P. C. (2011). *Handbook of social network analysis*. Sage.

Snijders, T. A. B., Pattison, P. E., Robins, G. L., & Handcock, M. S. (2006). New specifications for exponential random graph models. *Sociological Methodology, 36*(1), 99–153. https://doi.org/10.1111/j.1467-9531.2006.00176.x

Soleimanof, S., Rutherford, M. W., & Webb, J. W. (2018). The intersection of family firms and institutional contexts: A review and agenda for future research. *Family Business Review, 31*, 32–53. https://doi.org/10.1177/0894486517736446

Su, E., & Daspit, J. (2021). Knowledge management in family firms: A systematic review, integrated insights and future research opportunities. *Journal of Knowledge Management*. https://doi.org/10.1108/JKM-08-2020-0658

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. (2004). Knowledge, clusters, and competitive advantage. *Academy of Management Review, 29*(2), 258–271. https://doi.org/10.5465/amr.2004.12736089

ter Wal, A. L. J. (2014). The dynamics of the inventor network in German biotechnology: Geographic proximity versus triadic closure. *Journal of Economic Geography, 14*(3), 589–620. https://doi.org/10.1093/jeg/lbs063

Van Wijk, R., Jansen, J. J. P., & Lyles, M. A. (2008). Inter- and intra-organizational knowledge transfer: A meta-analytic review and assessment of its antecedents and consequences. *Journal of Management Studies, 45*(4), 830–853. https://doi.org/10.1111/j.1467-6486.2008.00771.x

Weimann, V., Gerken, M., & Hülsbeck, M. (2021). Old flames never die – The role of binding social ties for corporate entrepreneurship in family firms. *International Entrepreneurship and Management Journal, 17*(4), 1707–1730. https://doi.org/10.1007/s11365-021-00749-3

Whittington, K. B., Owen-Smith, J., & Powell, W. W. (2009). Networks, propinquity, and innovation in knowledge-intensive industries. *Administrative Science Quarterly, 54*(1), 90–122. https://doi.org/10.2189/asqu.2009.54.1.90

Yates, V. A., Vardaman, J. M., & Chrisman, J. J. (2022). Social network research in the family business literature: A review and integration. *Small Business Economics*. https://doi.org/10.1007/s11187-022-00665-y

Zahra, S. A., Neubaum, D. O., & Larrañeta, B. (2007). Knowledge sharing and technological capabilities: The moderating role of family involvement. *Journal of Business Research, 60*(10), 1070–1079. https://doi.org/10.1016/j.jbusres.2006.12.014

Zellweger, T. M., Chrisman, J. J., Chua, J. H., & Steier, L. P. (2019). Social structures, social relationships, and family firms. *Entrepreneurship Theory and Practice, 43*, 207–223. https://doi.org/10.1177/1042258718792290