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Do firms exchange knowledge through complementary or substitutive routes of diffusion?[1]

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Abstract

Studies on firms' relationships and network structures have attracted more and more attention from several scholars, but surprisingly little is known about the role played by heterogeneous knowledge ties among the same set of actors and to what extent they follow overlapping or different routes of exchanging knowledge. In this vein, an investigation of multiple knowledge networks in clusters is a fundamental approach to interpret the reasons for innovation and economic performance.

With an original dataset comprised of data collected by surveys directly administered in local wineries in the Montefalco wine region of Italy, this paper aims to analyse the roles played by different local knowledge ties, within a sector that is critically driven by the exchange of knowledge among economic actors.

Social Network Analysis and Exponential Random Graph Modelling were applied in order to investigate the driving forces of the knowledge flows. The empirical results show that different kinds of relationships positively impact the spread of knowledge, but they are different in magnitude, and they follow complementary routes of exchange rather than overlapping ones.

Keywords: multiple networks; knowledge diffusion; ERGM; industrial cluster; wine industry

JEL: D85, L14, L84

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1. Introduction

After decades of studies about pervasive, wide, and inclusive knowledge externalities (Marshall, 1920; Pyke et al., 1990; Rosenthal & Strange, 2004) and the advantages of *being there* (Gertler, 2003), recent literature on management, industrial marketing, economic geography, regional studies, and local development (among other related fields) has stressed that knowledge spreads imperfectly, unevenly, and selectively within regional and cluster contexts (Markusen, 1996; Giuliani, 2006; Corsaro et al., 2012; Geldes et al., 2015; Törnroos et al., 2017) because of the presence of different kinds of heterogeneities. Concerning this matter, Social Network Analysis (SNA) and its recent developments offer both theoretical and methodological instruments to unravel the relational structures at the root of this phenomenon.

In order to understand the roles played by relational architectures, both theoretical and empirical contributions have often investigated nodal, dyadic, and structural characteristics (Ahuja et al., 2012); however the literature has paid less attention to heterogeneous ties (Ahuja et al., 2012; Lorenzen & Andersen, 2012) even if they are a fundamental property of a relational set that involves different typologies of connections among two actors (Wasserman & Faust, 1994).

Among the few exceptions to the multiple ties approach to network analysis, Ferriani et al. (2012), in a study of a cluster of multimedia firms located in northern Italy, found out that both social interactions and economic exchanges are critical factors for the emergence of multiple ties within inter-organizational networks. Lorenzen and Andersen (2012) conducted an investigation on multiple ties in the Bollywood filmmaker industry. They demonstrated that diverse ties strengthen the positive performance related to uniplex (e.g., resource priority) ties and that they counteract negative effects related to the same multiple ties (as resource iteration and the lock-in effect) because they facilitate the search for knowledge. Capone and Lazzeretti (2018) detected that in the cluster of high technology applied to cultural goods in Tuscany, friendship and the network of technical advice positively impacted the likelihood of having a relationship for innovation. Contreras Romero (2018), studying a high-tech cluster in Chile, found a positive and statistically significant relationship between personal and business ties.

Consequently, we focus on an inter-firm network approach because the relational setting is a critical instrument of coordination. In fact, on the one hand, relationships impact the diffusion of specific knowledge; on the other hand, they rule the variability of access to knowledge across heterogeneous, cooperative, and competitive actors (Gnyawali et al., 2016). Thus, an economic actor in a multiple network environment operates between relational heterogeneity and interdependences.

In this work, we focus on this unexplored side, aiming to understand to what extent different kinds of ties can influence local knowledge diffusion and exchange. In particular, we distinguish between the relational content, as the substance of specific knowledge (i.e., technical), and several knowledge ties, as the drivers of multiple specific exchanges of knowledge (i.e., social and economic). This study contributes to the debate on inter-firm knowledge networks, innovation, and the competitiveness of firms proximate in space (Bathelt et al., 2004), it provides more in-depth information of knowledge networks through relational multiplicity (Snijders et al., 2013), and it offers new insights for business, management, and industrial marketing scholars on the critical roles played by relational structures (Nicholson et al., 2013) with a multiple network perspective.

The article focuses on the following research questions. What kind of ties promote the exchange of knowledge within knowledge networks? To what extent do they impact the exchange of knowledge? Do they follow different or overlapping routes?

We empirically explore these topics with an original dataset comprised of data collected by surveys directly administered in local wineries in the Montefalco wine region of central Italy. Specifically, we investigated this cluster because knowledge diffusion among co-localised economic actors critically affects the spread of contextualised and specific knowledge, the learning and innovation processes, and, in turn, the competitive advantage of a place hosting those actors (Liao, 2010; Nicholson et al., 2013; Brink, 2018). An Exponential Random Graph Model (ERGM) was applied to measure the impact of diverse knowledge ties on the technical knowledge network and to what extent they involve different or the same set of actors.

We organise our argument as follows: the next section presents the theoretical background and research hypothesis; Section 3 describes the data collection, methodology, and construction of the models' variables; continuing, Section 4 illustrates the empirical context; Section 5 shows the descriptive statistics and empirical evidence; and, finally, the discussion, main conclusions, and a few limitations are specified in Section 6.

2. Multiple knowledge ties and knowledge networks

2.1. Multiple knowledge ties

Over the last few decades, a portion of economic contributions have distinguished between formal/economic and informal/social ties (Owen Smith & Powell, 2004; Lin et al., 2012; Zhang & Zhou, 2013; McEvily et al., 2014), but a multiple ties approach to network analysis is still in its infancy, particularly from an empirical perspective. However, there are a few examples of well-known network-related contributions that have addressed this topic, at least indirectly. For example, Granovetter (1973) explored the roles played by two different kinds of dyadic interactions as weak ties (casual acquaintances) and strong ties (close personal friendship) to understand to what extent they are related and how they influence information diffusion, mobility, and community organization. Padgett and Ansell's (1993) contribution on the Florentine families in the Renaissance analysed two different categories of connections (marriage and economic ties), arguing that a large number of oligarch families (except the Medici) were linked with the others through both kinds of connections, and, when they were overlapping, they were more likely to possess close and holistic obligations. In the present paper, we explain network structures considering three fundamental typologies of ties by means of which they promote the exchange of knowledge: social ties (friendship), labour mobility (previous employment in another local firm in the same industry), and material exchange (sales or rental of machinery, raw materials, or semi-finished products).

2.2. Social ties and knowledge networks

Social ties are based on social and interpersonal relations, which several contributions have referred to as friendship and family relations among actors (Boschma, 2005). Several scholars have introduced this relational category in the industrial marketing management literature as one of the most critical determinants of business networks emergence and development (Batt, 2008; Westerlund & Svahn, 2008). Also, several cluster-related scholars have studied the role played by social ties in networks. In fact, a critical mechanism of knowledge diffusion among rival co-located firms is learning from the experience of the others (McEvily & Zaheer, 1999), particularly through interpersonal interactions among individuals.

However, spatial proximity does not automatically imply knowledge spillover among firms, but social connectedness in networks does (Breschi & Lissoni, 2001). Specifically, unplanned meetings within informal contexts – sometimes known as the "cafeteria effect" – are fundamental instruments for the spread of tacit and scarcely codifiable knowledge (Asheim, 1996; Cooke, 2001). This is even more significant within clusters where learning is a social process involving economic actors operating with similar cultural values (Audretsch & Feldman, 1996; Bathelt et al., 2004). In fact, typically, clusters host a high degree of connectedness among economic actors that are thereby embedded in specific places where relevant knowledge is highly tacit (Ter Wal & Boschma, 2011; Broekel & Boschma, 2011; Srećković & Windsperger, 2013).

Furthermore, other contributions have underlined that social ties are a good instrument to ease the exchange of knowledge among different actors who need a certain level of effort to understand *alter* knowledge (Srećković & Windsperger, 2011), especially if the other side of a relationship uses subtle or difficult phrases and concepts (Uzzi, 1997). Moreover, social ties are critical instruments for reducing risks once an actor aims to receive knowledge or transfer it to others (Larson, 1992), particularly those related to opportunistic behaviours (Uzzi, 1996). In this vein, Nooteboom (1996) argued that social ties are related to "goodwill trust", as the intention of related actors to perform according to a deal.

Several empirical contributions have identified the positive effect of social ties on different typologies of knowledge networks. For example, Dahl and Pedersen (2004) showed that social ties represent an important manner of knowledge diffusion in a cluster of wireless communication firms in Northern Denmark. Further, Bell (2005) demonstrated that informal friendship is a fundamental driver for innovation among mutual fund companies in the industry cluster of Toronto. Ter Wal (2013) showed the relevance of the exploration of knowledge (when knowledge is predominantly tacit) of the inventor network in the German biotech industry. More recently, Capone and Lazzeretti (2018) revealed that friendship and technical advice relationships impact the formation of innovation relationships in the cluster of high technology applied to cultural goods in Tuscany.

Thus, we propose the following hypothesis. HP1: Social ties between two firms have a positive impact on the likelihood that they exchange technical knowledge.

2.3. Economic ties and knowledge networks

The exchange of knowledge is also highly affected by formal ties based on different kinds of economic transactions (Uzzi, 1996). In this case, they are characterised by official administrative rules, explicit systems of incentives, and formal resource allocation (Lomi et al., 2013); however, they are fundamental instruments for potential future reciprocation of economic exchange because they take with them a guarantee of others' competence, credibility, and reliance (Chua et al., 2008). Particularly, the industrial marketing management literature suggests that formal exchanges based on contracts play a fundamental role in business to business markets and inter-firm networks (Seshadri & Mishra, 2004; Lin et al., 2012). Moreover, established formal economic relations may increase individual awareness of others' knowledge, particularly the one that is relevant for specific economic tasks (Austin, 2003). Economic ties are more likely to be suspended than social ties related to affective mechanisms if the relationship is not more beneficial or if it becomes problematic (Ahuja et al., 2012). Finally, Nooteboom (1996) claimed that economic ties are related to "competence trust", as the ability of related actors to perform according to an agreement; thus, this category of trust is critical for successful economic exchange.

Past contributions have focused on several economic-related ties of the spread of knowledge among co-localised firms. Breschi and Malerba (2001) identified the inter-firm labour mobility of workers as a critical economic factor for understanding the exchange of knowledge. Cantner and Graf (2006) argued (and empirically proved) that the labour mobility of scientists can predict the structure of a cooperation network of innovators in Jena. Also, Ter Wal and Boschma (2011) claimed that knowledge critically spreads among firms through labour mobility because recruiting employees who previously worked in other firms is an important way to access different knowledge. Almeida and Kogut (1999) further showed that workers often move within regions, leading to the result that local labour mobility is a fundamental way of regional and local knowledge flow. Moreover, Giuliani et al. (2005) added material and machinery exchanges as additional fundamental vehicles of knowledge diffusion within formal and planned environments. Nevertheless, to the best of our knowledge, the empirical efforts concerning this way of knowledge diffusion are much more limited.

Thus, we propose the following hypothesis. HP2: Economic ties between two firms have a positive impact on the likelihood that they exchange technical knowledge

2.4. Network multiplicity and exchange of knowledge

Focusing on an organizational setting, several contributions have stressed that knowledge is often difficult and costly to be exchanged because it needs a common communication base and a certain level of absorptive capacity (Cohen & Levinthal, 1990), and the cost of the multiple maintenance of different typologies of relationships can be even higher (Rothaermel & Alexandre, 2009). However, others have underlined that personally knowing the other part of the interaction through social ties and having learned how to work together through economic ties may mitigate these constraints (Hansen, 1999) because, in this way, they build a shared communication frame (Uzzi, 1997).

Moreover, knowledge shared through different knowledge ties, rather than only through one of them, may be more trusted (Granovetter, 1985); this is strictly related to knowledge extension because different networks are also representations of different role structures (Padgett & Powell, 2012), or multiplicity allows an actor to see actions by other actors playing multiple roles. Thus, it reduces uncertainty (Heaney, 2014). Consequently, in an environment characterised by multiple knowledge ties, social and economic ties can alternate their roles and their intensity over time. They can substitute each other's roles because they are intricately intertwined, and they may jointly affect the diffusion of knowledge (McEvily et al., 2014).

Ghosal & Nohria (1989) suggested that in relational organizational settings, social ties may provide integration across competing actors while economic ties are more likely to enhance differentiation. Hansen et al. (2005) widely explored the distinctions and similarities between social and economic ties, and they argued that social ties are affect-based and economic ties are cognition-based; thus, they are expressive and instrumental ties, respectively. In this vein, even if they assumed that both ties are critical factors for knowledge exchange, they also suggested that social ties have a higher level of intimacy, are more likely to create a sense of identity and social belonging, and have a stronger tendency towards mutuality. More recently, Ferriani et al. (2012) also discovered that both social and economic ties are drivers of multiplexity, but the former has a higher impact than the latter.

Thus, we propose the following hypothesis. HP3: Social ties have a higher impact on the exchange of technical knowledge than economic ties.

Finally, social and economic ties can simultaneously affect the exchange of knowledge because their routes of diffusion are critical aspects for understanding whether relational co-existence influences network structures. Uzzi (1996) suggested that different kinds of relationships among the same set of actors may be maintained over time because the presence of one typology of ties may foster and increase the stability of another typology of ties. He found that social ties promote the emergence of economic ties because they encourage an environment of trust and a common language.

Their co-existence may be guided by overlapping or differing routes of diffusion. On the one hand, overlapping structures may be costly and redundant because they lead to a waste of relational effort in creating a new link with a partner who is already tied through a different tie, and they may be risky because they involve the same set of actors (Laumann & Marsden, 1982). On the other hand, they may be an efficient instrument to decrease uncertainty towards other actors because they are likely to increase their reliability and their trustworthiness; furthermore, actors interacting with more than one kind of relationship may build an intense manner of exchanging knowledge based on a strong common knowledge base and language that leads to easier ways of absorbing other's knowledge and to an improvement in their stability (Lorenzen & Andersen, 2012). In this way, increasing returns can be present in the form of overlapping sets of relationships (Powell et al., 1996) because different actors secure important connections and critical resources flowing (Lomi & Pattinson, 2006). Complementary diffusion routes may also result in a reduction of dependency on a single typology of ties or a limited set of actors, thus, decreasing the risk of potential inward-looking mechanisms and negative lock-ins (Ferriani et al., 2012).

Thus, we propose the following final hypothesis. HP4: Social and economic ties are more likely to exist if they are overlapping. Table 1 presents the four research hypotheses.

Table 1: Research hypotheses

HP	Expected results
HP1	Social ties between two firms have a positive impact on the likelihood that they exchange knowledge
HP2	Economic ties between two firms have a positive impact on the likelihood that they exchange knowledge
HP3	Social ties have a higher impact on the exchange of knowledge than economic ties
HP4	Social and economic ties are more likely to exist if they are overlapping

Source: our elaboration.

3. Research design

3.1. Data collection

Even if different knowledge ties are not always easy to distinguish in practice (Podolny & Page, 1998), we attempted to overcome this problem by collecting primary data with an explicit distinction between different forms of relationships. A survey was administered in December 2017 and January 2018 within local wineries in an Italian wine cluster in central Italy (Montefalco region, Umbria). Telephone calls were made to increase the response rate and to schedule meetings directly in the wineries with the firm owners, technical professionals, or the agronomists (30 cases). If that was not possible, an online questionnaire was delivered (11 cases). Directly administered questionnaires had an average completion time of 40 minutes. An original list of 58 wineries was provided by the Consorzio Tutela Vini Montefalco, the local consortium responsible for coordinating more than 80% of local certified wine production in terms of hectolitres and all of the most important wine firms (Consorzio Montefalco Sagrantino, 2017). At the time of the data collection, seven of these wineries were definitively closed, or they were no longer producing wine; thus, the final database was comprised of 51 actors. In this case, 41 questionnaires were fully completed, reaching 80% of the total population.[5] Moreover, a semi-structured interview with the head of the local

[5] SNA methodologies are designed for complete networks, however, Kossinets (2006) proved that network properties are preserved with a response rate higher than 70%.

wine consortium ensured that we covered all of the most important wineries of the region. The very few wineries that did not agree to participate in the survey can be considered marginal in terms of their importance (for example, measured with size and reputation).

As in previous contributions (Giuliani & Bell, 2005; Morrison & Rabellotti, 2009; Hira and Aylward, 2013; Balland et al., 2016; Capone & Lazzeretti, 2018), different typologies of data were collected, including basic firm- and industry-level information, network data, and strategy-related information. Network data were collected with a combination of the free-recall method, where respondents are allowed to generate lists of names (for example, actors are asked to name all the actors they are linked with without choosing from a roster), and the fixed-choice method, where respondents can generate lists of names but with constraints (for example, actors are asked to name the first five other actors they are linked with) (Wasserman & Faust, 1994). Thus, the interviewer showed the complete list of other local wineries and then asked for a maximum of five ties. In this way, the respondent had a complete picture of all the possible linkages, and she/he was encouraged to nominate the main important relationships.

3.2. Methodology

Since theoretical and empirical efforts have prompted developments to model multiple relationships, especially in social networks, multiple network analysis has recently emerged as an auspicious research stream from the statistical perspective as well (Snijders et al., 2013). We implemented ERGM because of its greater applicability and power than other models; in particular, it is one of the preferable models in the case of small networks or a lack of longitudinal network data. Specifically, it is a stochastic model that allowed us to investigate the propensity for link formation as a continuous process over time, where the observed network is perceived as one realization from different potential networks built on similar characteristics (Robins et al., 2007). We executed ERGM using R-software with the STATNET-ERGM package (Handcock, et al. 2008) in order to analyse the role played by knowledge ties in technical knowledge transfer, considering node-, dyadic-, and structural-level factors. Moreover, it provided several different assessments on the quality of the model, such as goodness of fit (GOF) statistics, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

We followed Broekel and Hartog (2013) to estimate the models, relying on trial and error processes across different model specifications. The best model is a model that is stable, converges, and provides satisfactory GOF diagnostics concerning the observed network. We present the GOF diagnostics of the full model in Appendix 1.

3.3. Variables construction

The response variable was the technical knowledge network. It was based on the technical knowledge exchange regarding the production process and was determined by the answer to the question "what are the first five other local wineries among those listed to which you transfer technical knowledge to solve a problem in the production process?". We focused on technical knowledge transfer because its relevance has been proven in understanding the exchange of knowledge and the learning processes within clusters (Giuliani & Bell, 2005; Giuliani, 2010; Morrison & Rabellotti, 2009; Juhász & Lengyel, 2017). We focused on the spread of technical knowledge as one of the most critical contents of inter-firm exchanges. In particular, we studied the exchange of knowledge to solve specific problems because, in this way, firms develop capacities for mutual problem solving (Uzzi, 1997). In other words, we investigated firms in knowledge networks where they diffuse "[…] innovation-related knowledge, aimed at the solution of complex technical problems" (Giuliani, 2010, 265).

The explanatory variables included other three networks. First, the "social (friendship)" variable was based on friendship and was determined by the answer to the question "what are the first five other local wineries among those listed where you have friends regardless of professional relations?". Second, "labour mobility" was based on previous employment in another local firm in the same industry. Third, "material exchange" was based on sales or the rental of machinery, raw materials, or semi-finished products.

We also controlled for three main structural variables that are often included in ERGMs (Snijders et al., 2006). First, "edges" are the number of links at the network level, and they may be interpreted as the intercept parameter of the model. Second, "mutual" is the tendency of ties to be reciprocated; consequently, the variable needs directed ties to be estimated. Third, "triads" are captured by Geometrically Weighted Edgewise-Shared Partner (GWESP) statistics, and they are the number of triangles in the whole network, exploring how frequently two nodes are linked through another node (a two-path length connection).

Finally, some node-level variables and geographical proximity were modelled in the full model because several contributions have discovered that they play a critical role in knowledge transfer (Giuliani, 2010; Balland, et al. 2012; Hansen, 2015). In particular, we controlled for "firm size" and "firm experience" as categorical variables for the number of employees and the years worked in the wine industry within the region, as indicated by the survey respondents, respectively. "Firm local reputation" was a categorical variable for the sum of times a local winery was indicated by other wineries as having a high-level local reputation.

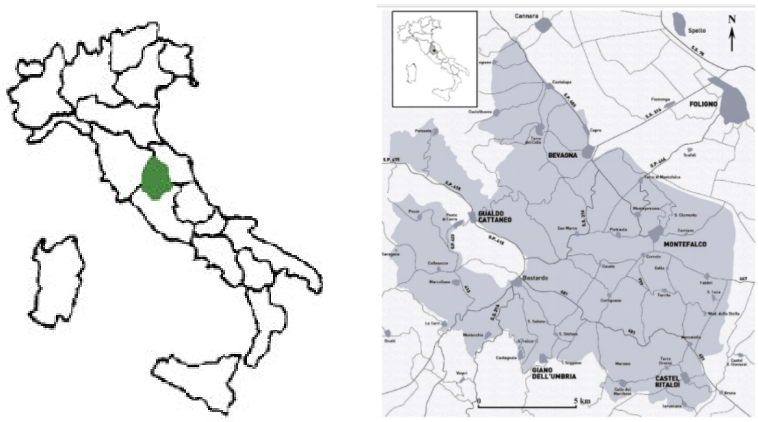
"Local R&D" and "external R&D" were binary variables for R&D developed in a research centre or university within or outside the region, respectively. "External consultant" was a categorical variable added when the interviewees answered as having sought advice from an external wine consultant. "Local wine institutions" and "external wine institutions" were binary variables that referred to wineries related to the local wine consortium and local wine routes (the local ones) or to the national wine tourist welcoming movement, the national sommelier association, and the national agricultural enterprises association, respectively. "Other local institutions" and "other external institutions" were binary variables referring to interviewees answers that local municipality, province, region (the local ones), national, or European institutions could be important actors to gain knowledge from, respectively. Finally, "geographical proximity" was the traditional categorical variable at the dyadic level for the physical propinquity between wineries based on the longitude and latitude of their locations.

4. The context

Montefalco is a village in the province of Perugia (Umbria region, Italy) surrounded by hills covered with a few grape varieties, particularly the *Sagrantino* variety, because the natural conditions (like soil conformation and a climate with hot, dry summers, fairly cold winters, and moderately rainy seasons) are very favourable for wine production. The local wine tradition has its roots in the 11th century, when the monks cultivated a wine grape imported from Turkey in their churchyard (in Italian, *sagrato*, from which the name *Sagrantino* comes). The "modern" wine history had its fundamental beginning around the 1980s, when the Montefalco area started being identified as a wine region due to the initiatives of two entrepreneurs (one was a furniture dealer, and the other was a textile trader before entering the wine industry) who, at the beginning of the 1970s, shifted wine production from sweet wines to dry ones. This process led to a denomination of origin (DOCG Montefalco, received in October 1979) and the establishment of a local consortium (Consorzio Tutela Vini Montefalco, founded in 1981). In this way, the Montefalco region began to be nationally and internationally recognised as a unique *terroir*, and a local identity began forming in that area where the residents started feeling embedded.

Nevertheless, the shift from quantitative to qualitative productions happened with the turn of the new millennium, and, over the last two decades, this wine region has entered the market of medium-high quality wines thanks to the production of the majority of local wineries (Consorzio Montefalco Sagrantino, 2017). Wine firms clustered in the Montefalco region operate in niche markets, and only a few bottles of *Sagrantino* are sold through large retailers in mass distribution while most of them have boutique stores, typical- and high-quality restaurants, and specialised wine stores as their main distribution channels. This system exploits product uniqueness and high-quality levels, which are reinforced by stories of tradition and authenticity as the main marketing message. In fact, after a survey, a wine producer claimed, "I more than doubled profits with a twenty percent increase in prices of high-quality bottles". In this vein, the wine tradition is the main cultural source of the region, and the wine industry (as well as the related sectors) is the most important local source of employment.

Figure 1: Montefalco wine region



Source: Consorzio Tutela Vini Montefalco website.

5. Empirical analysis

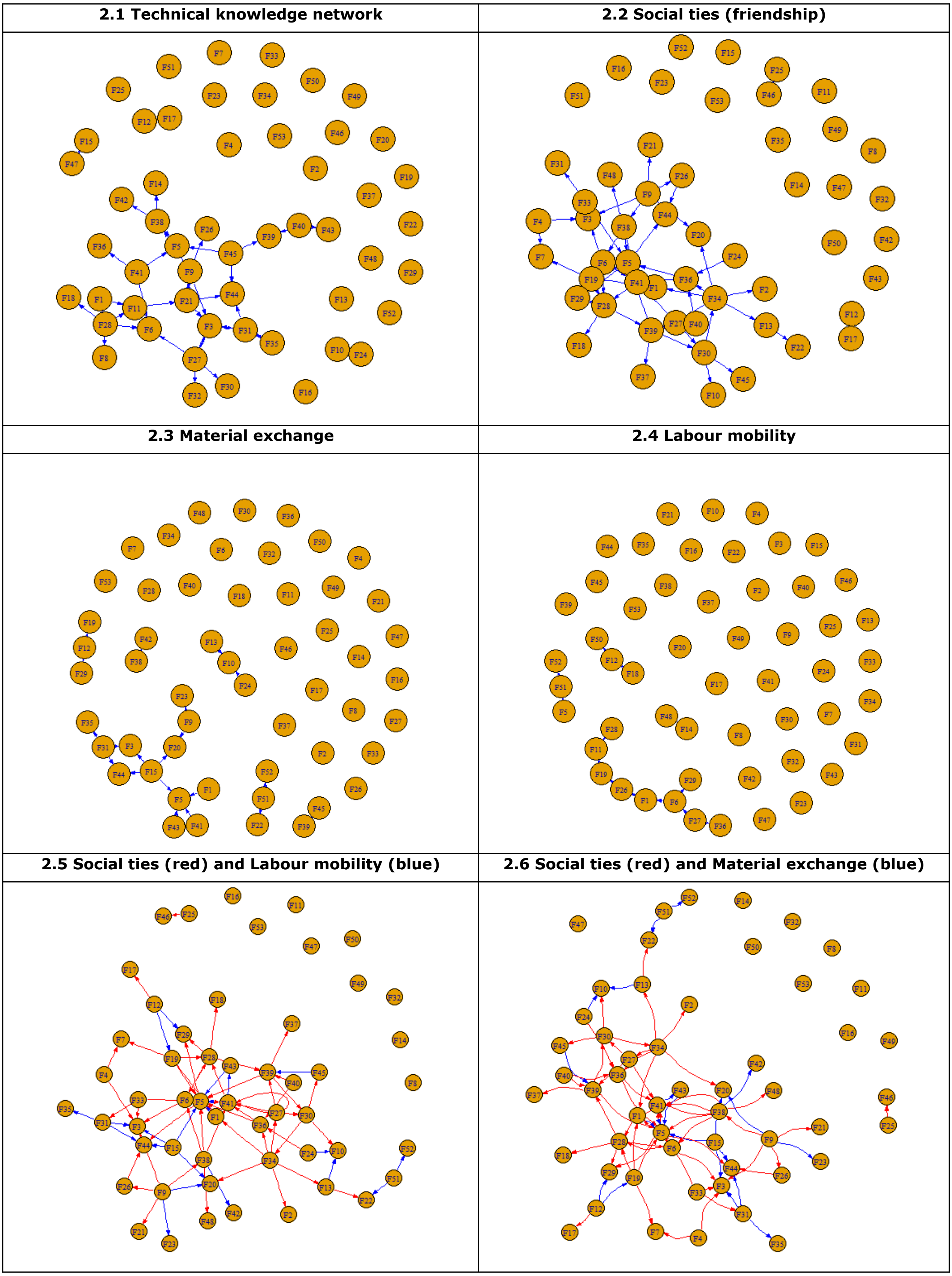
Table 2 presents descriptive statistics at the firm-level. It shows that the vast majority of the analysed sample was comprised of small firms in terms of employees that started operating within the region during the last five decades and particularly within the new millennium. Almost the totality of the firms were not part of a group and were typically family-run. Detailed firm-level descriptive statistics are presented below.

Table 2: Firm-level descriptive statistics of the analysed sample

Size (number of employees)	Small (1-19)	87%
	Medium (20-99)	10%
	Large (≥100)	3%
Decade of localization/birth	Up to 1969	15%
	1970s	21%
	1980s	0%
	1990s	15%
	2000s	36%
	2010s	13%
Organisational structure	Independent	90%
	Part of a group	10%

Source: our elaboration.

Figure 2: Network graphs



Source: our elaboration.

Descriptive statistics are visually confirmed by the graphs in Figure 2. Particularly, they present the technical knowledge network (2.1), social ties based on friendship (2.2), material exchange (2.3), and labour mobility (2.4). Graphs 2.5 and 2.6 present the union of the social ties network with the labour mobility and material exchange networks, respectively.

As we can see from the graphs, different sets of relationships present different network structures. Particularly, networks based on technical knowledge exchange and on social ties seemed to be denser than those based on labour mobility and on material exchange. In fact, the first two networks had a higher number of nodes linked by a relationship and a lower number of isolates than those based on labour mobility and material exchange. However, only networks built on technical knowledge exchange and social ties presented mutual ties (four ties and one tie, respectively) while the other two had no mutual ties.

Estimations are presented in Table 3. Model 1 includes the three main structural variables of the ERGMs and social ties. Models 2 and 3 substitute social ties with material exchange and labour mobility, respectively. Model 4 includes all of the three previous relations altogether. Models 5 and 6 include the three main structural variables and the union of social ties with material exchange and the union of social ties with labour mobility, respectively. Finally, Model 7 includes the three main structural variables, the three typologies of ties, and the control variables.

The full model is stable and converges. Following Hunter et al. (2008), we implemented GOF diagnostics to assess to what extent the parameters of the ERGM accurately predicted the observed network (the one based on empirical data). This was made by a comparison between the structure of the simulated network and that of the observed network. This model appears to be characterised by satisfactory GOF statistics for the distributions of the geodesic distance (the number of pairs for which the shortest path between them is of length k for each value of k), the edge-wise shared partners (the number of links in which two firms have exactly k partners in common for each value of k), and the in-degree (the in-degree distribution is due to the direct graph). In fact, data for the observed network overlapped the boxplots representing the distribution of the corresponding degrees across the simulated networks, and they were within lines corresponding to the 95% confidence interval. They are shown in Fig. 1 in Appendix 1.

Table 3: Summary of ERGM fit for technical knowledge network

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Edges	-4.829*** (0.203)	-4.755*** (0.193)	-4.604*** (0.186)	-5.086*** (0.232)	-5.025*** (0.226)	-4.893*** (0.212)	-5.992*** (0.018)
Mutual	2.933*** (0.639)	2.997*** (0.658)	2.939*** (0.657)	2.881*** (0.651)	2.836*** (0.661)	2.971*** (0.649)	2.698*** (0.015)
Triads	0.909** (0.319)	0.981** (0.372)	1.019** (0.377)	0.801* (0.361)	0.755* (0.348)	0.852* (0.365)	0.661*** (0.011)
Social (Friendship)	2.966*** (0.382)			3.102*** (0.416)			3.134*** (0.011)
Material exchange		3.751*** (0.486)		3.776*** (0.561)			3.871*** (0.017)
Labour mobility			2.601*** (0.790)	2.624** (0.932)			2.644*** (0.024)
Firm size							-0.017 (0.012)
Firm experience							0.009* (0.001)
Firm local reputation							0.015 (0.029)
Geograph. proximity							-0.001 (0.001)
Local R&D							0.755*** (0.028)
External R&D							-0.094*** (0.019)
Local wine institutions							-0.076 (0.039)
External wine institutions							-1.211*** (0.039)
Other local institutions							0.222*** (0.026)
Other external institutions							0.722*** (0.043)
Wine consultant							0.451*** (0.030)
Social& Material exchange					3.304*** (0.351)		
Social& Labour mobility						2.998*** (0.368)	
AIC	352.8	355	383.2	317.8	320.9	435.6	329.4
BIC	376.5	378.7	406.9	353.4	344.6	369.3	430.1

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05. Source: our elaboration.

Structural network variables demonstrated results in line with other empirical studies. All of the models presented negative and statistically significant coefficients for "edges" because they represent the density of the network in log-odds if other effects are excluded; in other words, the negative value is due to the fact that the actors were less prone to interact with each other in comparison to what is observed in random networks. Statistically significant and positive values for both the "mutual" and "triads" coefficients show that there is a tendency towards mutuality (as the tendency for ties to be reciprocated) and triadic closure (as the tendency for two nodes to be linked through another node) in the network.

The results presented in columns (1), (2), and (3) of Table 3 confirmed the first two hypotheses. Both the social ties and economic ties between two actors had a statistically significant and positive impact on the likelihood that they transferred technical knowledge; thus, they are critical knowledge ties. The results in column (4) refute the third hypothesis since material exchange ties were more likely to positively affect the technical knowledge network than social ties (even if social ties presented a stronger value than labour mobility).

Regarding the last hypothesis, no overlapping ties existed between the network built on social ties and the one on labour mobility. Only two wineries (F20 and F9) had simultaneously social and material exchange ties. This is enough to refute the fourth hypothesis and prevents empirically testing this aspect[6]; consequently, it leads us to move towards the complementarity interpretation. Columns (5) and (6) of table 3 present the results concerning joint networks, and they both had positive and statistically significant impact.

In column (7), we also controlled for several control variables, like size, experience, and local reputation at the firm level. Only the firm experience results were positive and statistically significant while it is not possible to confidently determine either the direction of the effects of the others or of the geographical proximity. Moreover, we controlled for the potential roles played by research centres and universities, consultants (because they usually play a critical role as sources of knowledge within wine industries), wine-related institutions, and other institutions, distinguishing between local and external ones. First, the results showed that actors were more likely to form knowledge ties if they were linked to local R&D sources (the corresponding probability was 0.68) than to external ones

[6] We also tested this aspect with a specific model, but the algorithm did not converge.

(the corresponding probability was 0.47). Second, it seems that wine-related institutions outside the wine industry were another driver of exchanging knowledge (but a statistically significant result was not detected for local wine-related institutions). Third, the results showed that the actors were more likely to form knowledge ties if they were linked to other external institutions (the corresponding probability was 0.67) than linked to local ones (the corresponding probability was 0.56). Finally, a critical role played by consultants was also detected.[7]

6. Discussion and conclusions

The aim of this work was to contribute to a better understanding of the mechanisms of the exchange of knowledge in geographical concentrations, such as clusters and industrial districts. Adopting a network perspective, we explored this critical issue from an innovative multiple ties approach involving different sets of relations comprised of social and economic ties. The empirical results showed that social ties based on friendship, economic ties based on labour mobility, and material exchange play fundamental roles in the local spread of knowledge but at different levels. In fact, once they were simultaneously investigated, it appeared that the local actors were more likely to provide knowledge to others if they met to sell or rent machinery, semi-finished products, and raw materials than if they knew each other on a friendship basis. In this case, labour mobility was the less critical knowledge tie. Moreover, social and economic ties did not overlap. This leads us to recall that different knowledge ties may contribute to the spread of knowledge by extending its diffusion throughout complementary routes.

We suggest that this study contributes to several related debates. First, we went one step further within organizational and industrial marketing studies towards contributing to a better understanding of to what extent a combination of social structures guided by informality and formality affects the sharing of knowledge (Ellis & Mayer, 2001; Inkpen & Tsang, 2005). The empirical results showed that knowledge exchange is not only involuntary but is also well-regulated by more formal exchanges within certain contexts. Moreover, the higher impact of

[7] The log-odds of any tie occurring are a coefficient of the model multiplied by the changes in the number of ties. The probability corresponding to coefficients of the model is computable as exp(coeff.)/(1+exp(coeff.)).

the typologies of ties based on formal/economic exchange than the others based on informal/social connections may have different effects. First, there may be a positive impact in the case of a crisis because social ties are more comprised of a sense of obligations, such as emotional needs, than economic ties. Moreover, they are more embedded in a social system where the local reputation plays a critical role, and every economic actor is likely to know every other economic actor; thus, they are less likely to lead the entire system to negative lock-in processes based on over-iterations and a scarcity of novel knowledge. This is even truer if we implement a multiple network analysis of the interconnections of different knowledge ties (substitutive vs. complementary relational structures); in fact, we suggest that our results in favour of complementary networks may be interpreted as a source of differentiation. Considering their heterogeneity, we also demonstrated that other different actors with potential novel knowledge are reachable through different relational patterns. Moreover, from an individual point of view, an alternative explanation for non-overlapping ties emerges. Since social and economic ties are particularly intertwined and sometimes difficult to be separately identified, an actor who does not belong to a network made of a kind of relationship or who has a peripheral position may be incentivised to form other typologies of connections as substitutes for the others. This may be an important alternative way to bridge the structural holes of a single knowledge network.

Second, within network studies, we theoretically and methodologically contributed to a shift from the observation of singular relations to inference on which kinds of connections influence given networks and to what extent they follow common or divergent relational structures (Lazega & Snijders, 2005). To the best of our knowledge, multiple networks have been attracting a low amount of attention in research (Hansen et al., 2005; Ferriani et al., 2013) even though an investigation of network multiplicity allows us to more deeply explore network structures (for a theoretical argumentation, see Ahuja, et al. (2012) and Lorenzen & Andersen (2012)). In fact, from a whole network perspective, a set of relations may seem to be structurally stable over time (for example, its descriptive network statistics may be relatively unchanged); meanwhile, it is possible that different sub-sets are co-changing in such a way that an effect in one set of relations is compensated by another phenomenon in the other. For example, an actor may delete a tie within a network and compensate for this with a new link within a different network, leading the entire system to appear structurally equivalent. In particular, we stressed the scientific relevance of a multiple relational perspective, and we suggested that ERGMs are useful methodological tools to study structures of networks comprised of different typologies of ties through which knowledge is transferred and that they allowed us to control for structural relational mechanisms other than node and dyadic features (Robins et al., 2007).

Third, within regional and local development studies, we suggest that different kinds of knowledge ties may stimulate the transfer of knowledge because they can benefit from proximity and advantages of repeated interactions (Boschma, 2012). This investigation tried to explore this issue, focusing on an industry where the knowledge-formation process is mainly incremental, and we found that different knowledge ties expose rival and cooperating economic actors to different knowledge with different degrees of novelty from other potentially remote and different actors. We proved that a multiple knowledge ties approach gave us the possibility to go deeper in understanding the collaboration-competition system typical of industrial districts and clusters (Becattini, 1990; Porter, 1998); in particular, we argued that multiple ties may be more conducive to transferring knowledge as a whole and to diffusing more specific knowledge for different strategical needs. Moreover, even if maintaining different sets of relationships is likely to have a high cost, different knowledge ties may be critical tools to face opportunism thanks to the trust present in both social and economic contexts while, at the same time, they are fundamental instruments to decrease dependency upon a single link.

Focusing on the wine industry, we can understand the reason why labour mobility fosters knowledge diffusion to a lesser extent than the other determinants. In fact, in this industry, workers sometimes move to other wineries because of tensions in the previous labour environment; thus, they are less likely to share fundamental information and specific knowledge. On the contrary, social ties and other categories of economic ties may have a stronger impact because they reduce transaction costs, they ease and increase efficacy of knowledge transferring, and they enhance the efficiency of mutual learning. These effects can be even higher if embedded in different sets of ties that simultaneously evolve.

To conclude, we theoretically designed a new picture of network multiplicity, and we empirically proved that different typologies of ties may have different impacts on local knowledge diffusion. In this vein, having discovered that they follow complementary routes, we suggest that they co-exist in several economic systems in being sources of innovation and differentiation of knowledge.

This work has some limitations. We studied only one cluster within an industry characterised by specific conditions, so we are not necessarily able to claim that the same results may be replicable in other clusters and other industries. Moreover, this work did not analytically explore whether one kind of relationship may be a bridge for another. In other words, we did not study whether one knowledge tie (for example, social ties) is more likely to bridge structural holes (for example, of economic ties). This may be an important field of research in the future.

Finally, these results may be considered by industrial marketing managers and local institutions that operate at the regional- or industry-level, since they suggest the possibility of implementing firms' strategic planning, and political instruments in favour of different forms of interactions among firms and in favour of more inclusive knowledge-sharing within networks with high levels of isolated firms. This is especially important for a sector like the wine industry in Italy, where consortiums of wine producers play a fundamental role in implementing formal relationships, inter-firm marketing co-operation, and trust among competitors.

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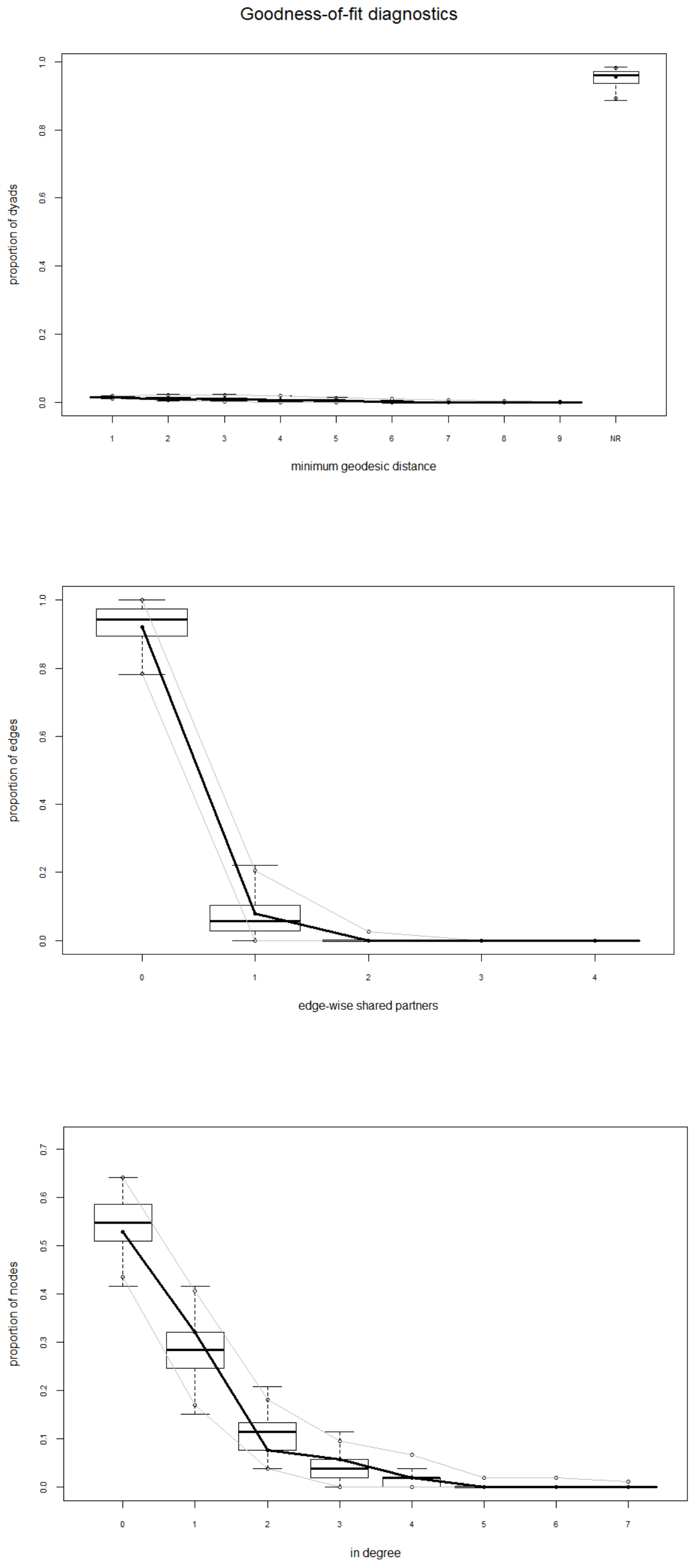
Appendix 1: Goodness of fit diagnostics for full model



Source: our elaboration.