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Network analysis: A concise review and suggestions for family business research

César Zamudio [a], Sergey Anokhin [a,d], Franz W. Kellermanns [b,c,*]

[a] Department of Marketing and Entrepreneurship, Kent State University, 800 East Summit Street, Kent, OH 44240, United States
[b] Department of Management, University of North Carolina-Charlotte, 9201 University City Boulevard, Charlotte, NC 28223-0001, United States
[c] INTES Center for Family Enterprises, WHU (Otto Beisheim School of Management), Germany
[d] Voronezh State University, Russia

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ABSTRACT

This article highlights the need for network-related research in family business. It provides a concise review of network related constructs and shows potential applications for family business research. It further highlights issues related to data collection and analysis. The article concludes with examples of how network research may extend recent studies and provides an agenda for future research.

The importance of social capital has long been stressed in family firm research (e.g., Pearson, Carr, & Shaw, 2008; Sirmon & Hitt, 2003; Zahra, 2010). Indeed, a focus on relationships among key family members and the family's relationship with outside stakeholders seems like a natural focus for family firm research, which stresses the importance of such connections as key advantage for family firms (e.g., Habbershon & Williams, 1999; Sirmon & Hitt, 2003). In addition, the socio-emotional wealth (SEW) perspective (Gómez-Mejía, Haynes, Núñez-Nickel, Jacobson, & Moyano-Fuentes, 2007), which is developing into a major focus in family business research, also stresses the benefits of binding social ties (Berrone, Cruz, & Gómez-Mejía, 2012), both within the family and with outside constituents.

The field of strategic management (e.g., Nahapiet & Ghoshal, 1998; Tsai & Ghoshal, 1998) has embraced network research. Similarly, general entrepreneurship (e.g., Aldrich & Zimmer, 1986; Greve & Salaff, 2003; Jack, 2010) and small business researchers (e.g., Curran, Jarvis, Blackburn, & Black, 1993; Donckels & Lambrecht, 1995) have conducted network-based research. However, although family firm research stresses the importance and performance implications of social capital (Chrisman, Chua, & Kellermanns, 2009), very limited empirical (and theoretical) network-based research has been conducted in the family firm literature (for exceptions, see Della Piana, Vecchi, & Cacia, 2012; Padgett & Ansell, 1993).

To address the lack of network research in the family firm literature, our article adopts a three-pronged approach. First, we review network-related research and highlight the key constructs utilised in the literature. Corresponding to each construct, we briefly highlight potential applications to family firm research. Second, we review data related issues and sampling techniques used in this line of research. Third, we provide additional areas for family firm research, and show how current studies could benefit from network research.

1. Network constructs

1.1. General comments

The role of relationships among firms and other institutions has gained increased attention over the last decade in the social sciences in general (Borgatti, Mehra, Brass, & Labianca, 2009) and particularly in business (e.g., Achrol & Kotler, 2012; Greve & Salaff, 2003), as these relationships may play a role in explaining firm performance. Empirically, this exploration requires data that describes firms' relationships – their social networks – which are generally constructed using information on N firms and (potentially) M relevant "events": other institutions, places, etc., that these N firms may relate to in some way. Three types of datasets may be constructed. The first type is a *case-by-case* dataset: an $N \times N$ matrix that records which of the N firms are related and (possibly) the strength of their relationships – for

* Corresponding author at: Department of Management, University of North Carolina-Charlotte, 9201 University City Boulevard, Charlotte, NC 28223-0001, United States. Tel.: +1 704 687 1421.
E-mail address: kellermanns@uncc.edu (F.W. Kellermanns).

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instance, whether firms are allies and the duration of their alliances. The second type is a *case-by-affiliation* dataset: an $N \times M$ matrix that records firms' participation in different events – for example, which of the N firms have an account in which of M banks (Levine, 1972). The final type is an *affiliation* dataset: an $N \times N$ matrix that holds the number of times firms coincided in the same events – for example, which of the N firms have an account in the same bank.

Social network data can be constructed using historical records, survey data, or both. In what follows, we will frame our discussion around a social network of family businesses, represented by a $N \times N$, case-by-case matrix denoted by X. Within matrix X, the rows $i = 1,2,\ldots,N$ and columns $j = 1,2,\ldots,N$ both represent each one of the N firms in the data. In social networks, these are generally known as *nodes*. When we refer to a focal firm of interest, we will denote it as f. A single cell of the matrix X, denoted by x_{ij}, represents the potential relationship between firms i and j, that is, the "line" and "weight" of the line between firms i and j, if represented graphically. In social networks, these are generally known as *edges*.

Care must be exercised when interpreting the meaning of the relationships within X, as there are two types of social networks. If a social network is *directed*, the observed relationships among firms imply directionality: for example, if firm i sends a resource to firm j, but not the converse, then $x_{ij} = 1$ but $x_{ji} = 0$. This definition implies that a cell $x_{ij} = 1$ in a directed network is read as "whether firm i sent a resource to firm j". If a social network is *undirected*, then the observed relationships among firms imply linkage but not directionality: for instance, if firm i and firm j are members of the same credit union, then $x_{ij} = x_{ji} = 1$. When the properties of the network as a whole are relevant, this is termed *network-level* analysis and consists of aggregate metrics. When the properties of individual members of the network are relevant, this is termed *ego-level* analysis, and metrics for each member of the network are computed (Wasserman & Faust, 1994). Both approaches may be used simultaneously. Regardless of the type of social network under examination or the analytical approach involved, social networks exhibit properties that, once computed, may be related to firm performance. For example, one may shed light on whether belonging to a dense group of businesses (perhaps in a regional association) or locating a new business in the vicinity of existing allies has an impact on sales or innovation. We outline some of the most relevant properties of social networks below.

1.2. Key network constructs

Weighted and unweighted networks: Social networks may be weighted or unweighted. Recall that the matrix X records all the relationships among all members of the social network. If these relationships are all described using zeros and ones, then the network is *unweighted*, and therefore matrix X describes whether any two members i and j are related. On the other hand, if the relationships are described by either zero or a set of numbers larger than zero (for example, the number of transactions among each firm in X), then the network is *weighted*. As is discussed below, the distinction between unweighted and weighted matrices[1] is not purely statistical, as ties with greater weights indicate stronger relationships among firms.

Density: The analysis of a network's density yields the general level of linkage among its members (Scott, 1991). A complete network where every firm is related would exhibit the highest density possible, specifically $\binom{N}{2} = \frac{N(N-1)}{2}$. The density of a social network may be calculated using

$$\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij}}{N(N-1)} \tag{1}$$

which is the ratio between the total observed number of relationships in a network and the maximum number of relationships possible in that network. This formula applies to both directed and undirected networks (Iacobucci, 1994). Density may also be calculated for subgroups within a network (for instance, industry-by-industry density) as

$$\frac{\sum_{i=1}^{N_s}\sum_{j=1}^{N_s} x_{s,ij}}{N_s(N_s-1)} \tag{2}$$

which is an expression close to Eq. (1), but where only the relationships among the N_s firms in subgroup s, denoted by, $x_{s,ij}$, are used. The level at which density is calculated depends on the research questions asked. For example, one could propose that the industry-specific density of relationships among firms is related to innovation, thus leading to the measurement of industry-level densities. Alternatively, one could conjecture that overall density is related to innovation instead and work with network-level density. Finally, one could use both network and industry-specific densities as independent variables to control for different sources of variation. In either case, one would typically regress the relevant density scores on innovation.

To illustrate the above point, consider Padgett and Ansell's (1993) seminal study on family structure in Renaissance Florence. The authors empirically chronicled the ascent of the Medici among Florentine families by recording the marriage network of the era. Among the 16 most prominent Florentine families, the authors compiled[2] whether there was any marriage among any of them, resulting in an undirected, unweighted network, as in Breiger and Patison (1986). Fig. 1 graphically displays these relationships. There are 20 ties in total among 120 potential ties, which implies a density of 0.167 applying Eq. (1).[3] The average degree of the network is 2.5, implying that families have between two and three marriage relationships among other families in the network (Iacobucci, 1994). The shapes that represent each family are described when we discuss community detection.

Centrality. *Generalities*: When a firm is deemed "central", it means the firm is more prominent than the rest. Furthermore, firms may be locally or globally central. A locally central business is one of high prominence in its immediate vicinity, whereas a globally central firm is prominent throughout the social network. In either case, a firm's centrality is generally interpreted as its global or local level of influence. Consequently, relationships in a firm's immediate vicinity are as important as the relationships a firm could establish by using firms it is related to as a path to others across the network. Several types of centrality may be calculated, with different assumptions and potential managerial implications. In the following, we focus on centrality metrics for undirected networks.

[1] A third possibility is to construct a matrix where each element x_{ij} may take the values of −1, 0 and 1, indicating a negative valence, the absence of a relationship, or a positive valence, respectively (Iacobucci, 1994). In these types of networks, a tie of negative valence may indicate a rivalry and a positive valence a friendship, but tie weight is not captured.

[2] The Florentine families dataset, among many others, comes packaged into the UCINET software (Borgatti, Everett, & Freeman, 2002). This and other social network analysis packages are briefly discussed at the end of this section.

[3] Note that the sum total of the values in the Florentine matrix is 40 (i.e. $\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij}$). However, because the matrix is undirected, the total number of *ties* is 20. Applying Eq. (1) uses the sum total of values, thus requiring to divide 40 by $N(N-1) = 240$, which yields an identical result.