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Competitive Research Article

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An Integrated Approach to Studying Multiplexity in Entrepreneurial Networks

Abstract: Multiplexity occurs in entrepreneurial networks when flows interact within and across relationships. It defines how these networks function and evolve and cannot be examined by studying network structure or flows separately. Despite the growing recognition of the importance of multiplexity, related research has remained limited and lacks an integrated approach to simultaneously examine structure and flows, thus restricting our understanding of entrepreneurial networks. We propose an integrated approach for conducting inductive studies into multiplexity, involving an adaptation of the "business networks" conceptual model, the configuration theory perspective, and the Q-analysis method.

Keywords: entrepreneurial networks, multiplexity, configuration theory, Q-analysis

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1 Introduction

Entrepreneurial networks are considered to be important organizational forms that both reflect and enable the strategic goals of entrepreneurs (Ostgaard and Birley 1994; Hoang and Antoncic 2003; Hill and Birkinshaw 2008). They are important to entrepreneurs for accessing, exchanging, and transforming resources in order to establish firms (Kanter 1983; Birley 1985; Aldrich, Rosen, and Woodward 1987; Ozdemir et al. forthcoming) and overcome liabilities of newness and smallness (Stinchcombe 1965; Stuart, Hoang, and Hybels 1999). By network, we mean the set of relations between the entrepreneur and their direct

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contacts, including interrelations between these direct contacts, i.e., the entrepreneur's ego-network. By entrepreneur, we include a person who "carries out new combinations" to develop their venture (Schumpeter 1934, 78).

Research on entrepreneurial networks has focused either on network structure or network flows, and thus not captured the role of multiplexity in the function or evolution of the entrepreneur's network (Slotte-Kock and Coviello 2010). The structural perspective focuses on *who* is a part of the network (i.e., which actors), the topology of their relationships, and the entrepreneur's position in the network (e.g., Shepherd 1991; Soh 2003; Al-Laham and Souitaris 2008). This perspective emphasizes how network positions enable aggregation and combination of resources and is dominated by quantitative methods such as social network analysis (SNA), and typically operationalizes only one type of relationship per study (e.g., investment, patent co-authorship, or strategic alliances). Such structural methods are limited in their ability to capture the diversity of interactions between the various actors and flows that comprise organizational and inter-organizational systems (Fiss 2007, 2011), including entrepreneurial networks.

The flow perspective focuses on *what* types of resources are involved in individual relationships, and on *how* these diverse resources are put to use, exchanged or transformed (e.g., Larson 1991; Yli-Renko, Sapienza, and Hay 2001; Hite 2005). Research using the flow perspective typically focuses on how multiple exchanges occur and interact within a single relationship using qualitative research methods (e.g., Larson 1991; Hite 2003, 2005). This focus means de-emphasizing and thus omitting interactions of flows across relationships. Therefore, research using this perspective is limited in its ability to describe or explain how multiplexity affects the overall network or its evolution.

Both these network perspectives have proven to be theoretically useful for understanding how entrepreneurial networks vary, and which network position or resources matter when. However, reliance on either of the two dominant perspectives omits multiplexity at the network level, and thus limits our ability to answer research questions about how entrepreneurial networks function and evolve. Recent reviews note the limitations of the two dominant perspectives and criticize that "the characteristics of individual actors [and their flows], to the extent that they are discussed at all, have tended to be treated as residues of social structure" (Kilduff and Brass 2010, 332), and that omissions of network multiplexity result in network research that is "unrealistic" (Shipilov 2012, 216). In this study, we apply the concept of multiplexity to the level of the entrepreneur's network by defining network multiplexity as the interaction of flows within *and across* relationships.

This paper is similar to other methodology papers (e.g., Siggelkow 2002; Fiss 2007; Crawford 2009; Jack 2010) in that it provides a contribution that guides scholars to adopt a new approach with which research questions can be

addressed more accurately, including entirely new research questions. In particular, we propose an integrated approach to studying entrepreneurial network structure and flows, in order to enable more holistic and realistic research about how entrepreneurial networks function and evolve. Our approach proposes an adaptation of the "business networks" conceptual model (Håkansson 1989; Slotte-Kock and Coviello 2010), draws on arguments in configuration theory perspective, and introduces Atkin's Q-analysis method (1974) to entrepreneurship scholars. This reconceptualization, perspective, and method all simultaneously consider the elements that comprise the structure (actors) and flows (resources and activities) in entrepreneurial networks and their combination.

By adopting a more holistic approach, as proposed here, we hope to enable researchers to explore research questions related to how entrepreneurs evaluate potential resource flows in context of their existing network. How do they decide who to seek which resources from, and how do those resources affect the rest of their network? Such questions are of extreme importance to any entrepreneur who (for example) is deciding whether to seek capital (i) from investors who may also provide advice and affect the direction of the business, (ii) or from banks who take a more hands-off approach, (iii) or from strategic partners who may want exclusive access to the resulting products or services. In many cases, a give resource (e.g., capital) comes with strings attached. As researchers, our ability to conceptualize such interactions remains limited. Consequently, our theories have remained limited in explaining the complex nature of entrepreneurial networks and their evolution.

We present our arguments and contributions in four major sections. In the first major section, we review the literatures on (i) multiplexity, (ii) conceptual models suited to multiplexity research, and (iii) theoretical perspectives suited to multiplexity research. In the second major section, we explain the merits and mechanics of the Q-analysis method (Atkin 1974) using simplified illustrative examples. Third, using data from an existing case study, we demonstrate an application of the method. Theory development based on this demonstration is beyond the scope of this paper. Lastly, we identify new directions for research on the effects of multiplexity, and its role in the function and evolution of entrepreneurial networks.

2 Literature review

2.1 Multiplexity

Multiplexity is an important, yet often ignored, feature of entrepreneurial networks and their evolution (Shipilov 2012). Research on entrepreneurial networks

has historically been challenged due to a "tendency toward methodological simplicity" (Coviello and Jones 2004, 502). As a result, "most studies [...] take an oversimplified view of networks by *assuming away their multiplexity* [and thus] are missing a possibility to examine how multiple kinds of relationships could simultaneously affect network dynamics and network outcomes" (Shipilov 2012, 215, emphasis added).

In general, multiplexity occurs when multiple types of relationships overlap within the same set of actors, thus causing the relationships and actors to be interdependent (Kapferer 1969; Doreian 1974; Koehly and Pattison 2005). Its occurrence can be traced back to the fact that people, including and especially entrepreneurs, "generally [have] more than one relation simultaneously operating" (Harary 1959, 402). It is particularly important for entrepreneurial networks, since entrepreneurs use their networks to access and combine diverse types of relationships (e.g., Birley 1985; Lechner and Dowling 2003).

Multiplexity is typically defined at the dyad level as the occurrence or interaction of two or more different types of relationships between the same two actors (Rogers and Kincaid 1981; Hoang and Antoncic 2003; Hite 2005; Grossman, Yli-Renko, and Janakiraman 2010). Confusingly, some prior uses and definitions of "network multiplexity" imply a network-level concept, but remain focused on the dyad level (Krohn, Massey, and Zielinski 1988; Dhanaraj and Parkhe 2006). To illustrate dyadic multiplexity, we draw on a case study from the literature, in which Chad at DataTools describes the overlapping roles of a partner firm:

> I'm selling my products through them. But I'm also doing work for them. So it kind of goes both ways... They are [also] a competitor... In this whole relationship, they are actually every single one of these that I can think of [supplier, customer, vendor, broker, previous employer]. (p. 28 in Hite 2003)

In this paper, we define ***network multiplexity*** as the interaction of exchanges within *and across* relationships. This is inclusive of dyadic multiplexity as well as situations in which a relationship of one type with one actor is interdependent on one or more relationships of other types with other actors. Our definition is also consistent with the "three key premises" for considering multiplexity at the network level: "(a) organizations are simultaneously embedded in different kinds of relationships, (b) these relationships are interdependent [i.e., they interact] and (c) this interdependence influences organizations" (Shipilov 2012, 215). Network multiplexity has direct implications for how networks function and how changes propagate throughout networks.

2.2 Conceptual models

Hoang and Antonic (2003, 177) posit that "current work seeking to explain entrepreneurial success is limited by considerable conceptual vagueness regarding the resources [...] and how we measure the networks that provide those resources." They offer a "general" definition of a network as "consisting of a set of actors and some set of relationships that link them" (2003, 167). However, this definition also remains vague about the nature of the relationships, and may include, but does not clearly capture multiplexity at the dyad or network level.

A conceptual model that is more aligned with network multiplexity research is offered by Yli-Renko and Autio (1998), in which "the actors' resources are bound together by activities, which form the links between the [entrepreneur] and the other actors in the network" (p. 255). In this model, relationships involve activities in which resources are put to use, exchanged or transformed, and are able to capture dyadic multiplexity, as for example in Yli-Renko's later work (e.g., Grossman, Yli-Renko, and Janakiraman 2010). However, this model and its associated figure indicate an assumption that the activities and resources in each relationship are independent of those in other relationships. Therefore, the model does not meet Shipilov's (2012) second key premise that relationships are interdependent, and thus does not capture network multiplexity.

In order to capture multiplexity within *and across* relationships, we propose an adaptation of Håkansson's (1989) conceptual model. Slotte-Kock and Coviello (2010) also highlight this conceptual model as being useful to entrepreneurship scholars for studying network multiplexity and network evolution, because it can be used to "understand change within relationships as well as across relationships and the impact of change on the wider network" (p. 46). Our adaptation clarifies what is meant by "actor", "resource", and "activity" in context of entrepreneurial networks, as visualized in Figure 1. Otherwise, the element types and their inter-connections are the same as in the original model.

Håkansson's "business networks" model was developed in the industrial marketing literature (known as the IMP Group), and views networks as integrated systems of "*actors* linked together by their performance of complementary or competitive [...] *activities*, which implies that certain *resources* are processed as a result of other *resources* being consumed" (Håkansson 1989, 16, emphasis added). As later articulated in the IMP Group's seminal summary of 30 years of research based on the conceptual model, the "three [actor, resource, activity] layers are inter-connected: Each affects and is affected by the constellation of resources, pattern of activities and web of actors in the wider network"

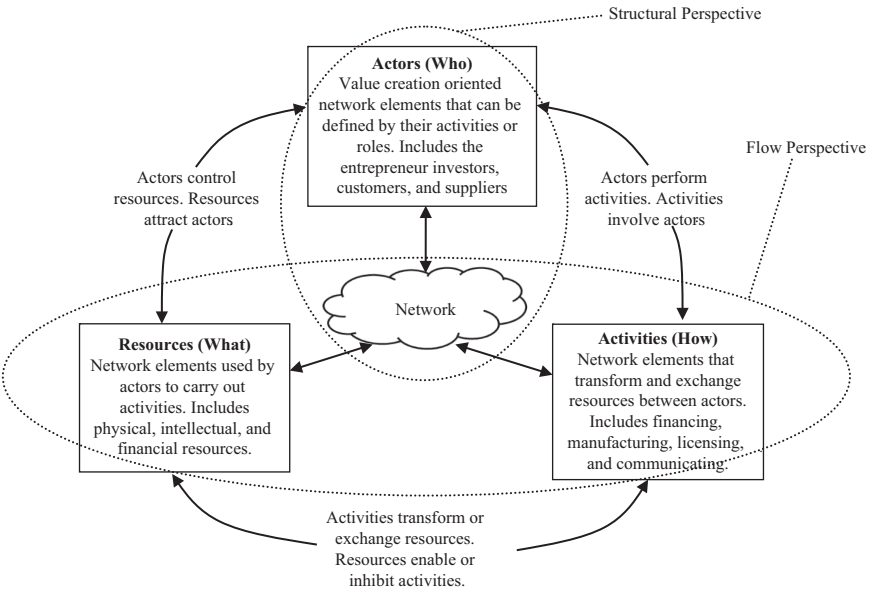

Figure 1: Conceptual model of entrepreneurial networks (adapted from Håkansson 1989)

(Håkansson et al. 2009, 33). Because of this layering of multiple actors, resources, and activities, the model is inclusive of dyadic and network multiplexity. Over the next sections, we review the two dominant network perspectives, and use our representation of Håkansson's model as a reference point for discussing the extent to which these perspectives integrate structure *and* flow elements, and thus network multiplexity.

2.3 The structural perspective

Structural studies tend to focus on the topology of interconnections between actors (e.g., Lechner, Dowling, and Welpe 2006; Rothaermel and Deeds 2006; Watson 2007), usually using quantitative SNA methods (Wasserman and Faust 1994; Carrington, Scott, and Wasserman 2005). This structural focus is achieved by investigating one type of flow per actor, such as supplies (Uzzi 1996), bank loans (Uzzi 1999), R&D knowledge (Powell, Koput, and Smith-Doerr 1996; Al-Laham and Souitaris 2008), board member advice (Zaheer and Bell 2005), or joint product development knowledge (Soh 2003). Structural studies have revealed that favorable outcomes can be achieved by being in dense networks (Lorenzoni and Ornati 1988; Gnyawali and Madhavan 2001), larger networks

(Watson 2007), by occupying central network positions (Soh 2003; Al-Laham and Souitaris 2008), and bridging multiple unconnected parties (Burt 1992; Zaheer and Bell 2005).

This perspective and its reductionist focus on one type of flow at a time may be rationalized by empirical observations that "entrepreneurs tend to label their economic exchange partners and classify them according to the main benefit that the partner provides" (Lechner, Dowling, and Welpe 2006, 529). However, by focusing only on who is connected to whom, and by being imprecise about the diversity of the their flows and interconnections thereof, such a reductionist rationalization inhibits exploring many research question related to network multiplexity and the evolution of the entrepreneurial networks. In comparison to our conceptual model, this perspective only considers the portion contained in the upper dotted ellipse (Figure 1).

To visualize the structural perspective, Figure 2 shows two simplified entrepreneurial networks: one in which the entrepreneur (E) is connected to 4 investors (I) who are involved in financing the entrepreneur's venture (Figure 2(a)) and one with 5 customers (C) who are buying the entrepreneur's products (Figure 2(b)). Each type of flow (financing vs. buying) is treated as an entirely separate network, and thus represented across two separate network figures. In reality, an entrepreneur's need to access venture capital is interdependent on the revenues they can generate. Overall, the structural perspective takes multiplexity for granted, and thus misses at least half of the story of how entrepreneurial networks function and evolve.

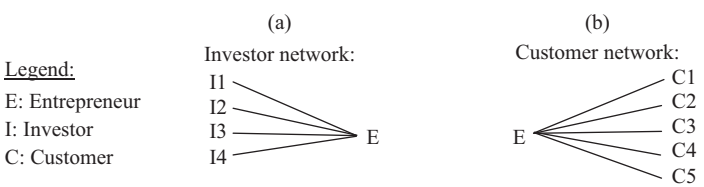

Figure 2: Structural perspective (simplified examples)

2.4 The flow perspective

The flow perspective acknowledges that entrepreneurs combine a diverse set of resources (e.g., Hoang and Antoncic 2003; Lechner and Dowling 2003; Franco and Haase 2011) but is limited to studying each relationship separately (e.g., Larson 1991; Yli-Renko, Sapienza, and Hay 2001; Hite 2005). Methodologically, flow studies tend to use qualitative methods such as ethnography and case

study analysis to examine the interactions of flows within individual relationships and their evolution (e.g., Larson 1991; Hite 2003, 2005). They are limited in their ability to systematically capture the structural context and patterns of interactions across relationships (see Lorenzoni and Lipparini 1999 for a notable exception). In essence, this perspective assumes away the surrounding structure of the network to focus on the elements in the lower dotted ellipse of our conceptual model (Figure 1).

Figure 3 visualizes two separate relationships using the flow perspective: one investor relationship and one customer relationship. Each of these relationships involves multiple interacting flows, described by the resources and activities mentioned in the figures. Even though some of the elements are common across both relationships (e.g., entrepreneur and cash), this perspective treats each relationship separately and is therefore best represented as two figures. Despite this separation, the flow perspective has the potential to be extended to study network multiplexity by recognizing actors, resources, and activities that are common across multiple relationships.

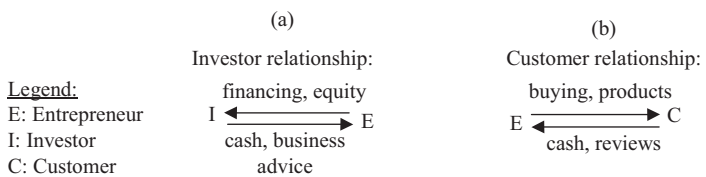

Figure 3: Flow perspective (simplified examples)

2.5 The configuration theory perspective

The configuration theory perspective posits that organizational systems are "composed of tightly interdependent and mutually supportive elements such that the importance of each element can best be understood by making reference to the whole configuration" (Miller and Friesen 1984, 1). We relax the assumption of "tight" interdependence by recognizing that there are varying degrees to which elements are directly interdependent, and that elements may be indirectly interdependent via intermediate (directly interdependent) elements. This variance of interdependence is also recognized in Siggelkow's (2002) detailed descriptive analysis of the performance and evolution of the Vanguard Group as a configuration. In this study, Siggelkow "treated organizational systems as networks consisting of nodes (organizational elements) and connecting edges

(interactions)" (2002, 134), and specifically investigated the degree to which elements were more or less "core".

We apply the configuration theory perspective to entrepreneurial networks, by simultaneously considering how both the structure and flow elements interact to develop holistic and coherent configurations (Meyer, Tsui, and Hinings 1993; Snow, Miles, and Miles 2005). By holistic we mean that the network is conceptualized as a single system of interacting elements – *actors* (structural perspective), *activities*, and *resources* (flow perspective) – as opposed to studying these elements in isolation. By coherent we mean that of the different permutations and combinations of structure and flow elements that might be hypothetically possible, only a fraction will be viable and interesting. The theoretical value in discovering holistic and coherent images of networks as configurations is that their attributes are associated with internal consistency and external fit. These attributes are, in turn, related to viability and effectiveness (Miller and Friesen 1984; Meyer, Tsui, and Hinings 1993).

Such holism and coherence of entrepreneurial networks and their network multiplexity has "important conceptual, evolutionary or normative implications" (Miller 1996, 507). The evolutionary implications are particularly important, because entrepreneurial networks have high levels of dynamism (e.g., Elfring and Hulsink 2007; Jack, Dodd, and Anderson 2008; Jack et al. 2010), largely because entrepreneurs need to access different resources over time (Lechner, Dowling, and Welpe 2006; Rothaermel and Deeds 2006; Watson 2007). By thinking through the implications of network multiplexity, entrepreneurs can holistically explore potential synergies or conflicts with other relationships in their network such that the network as a whole remains viable, effective, and coherent.

Building on the previous example in Figures 2 and 3, we can visualize the same simplified network as overlapping sets of interacting elements (Figure 4(a)) or as interconnected polyhedra (Figure 4(b)) (see also Johnson 1990a for similar examples). These visualizations draw out which elements are common across relationships and are therefore more "core" to the overall network. These common elements form the basis on which to investigate network multiplexity, and identify (structure and flow) elements through which changes propagate throughout the network.

Unlike (quantitative) structural studies or (qualitative) flow studies, configurational studies usually employ set-theoretic methods (Ragin 2000; Fiss 2007, 2011) to "express complicated and interrelated relationships among many variables without resorting to artificial oversimplification of the phenomenon of interest" (Dess, Newport, and Rasheed 1993, 776). Standard set-theoretic

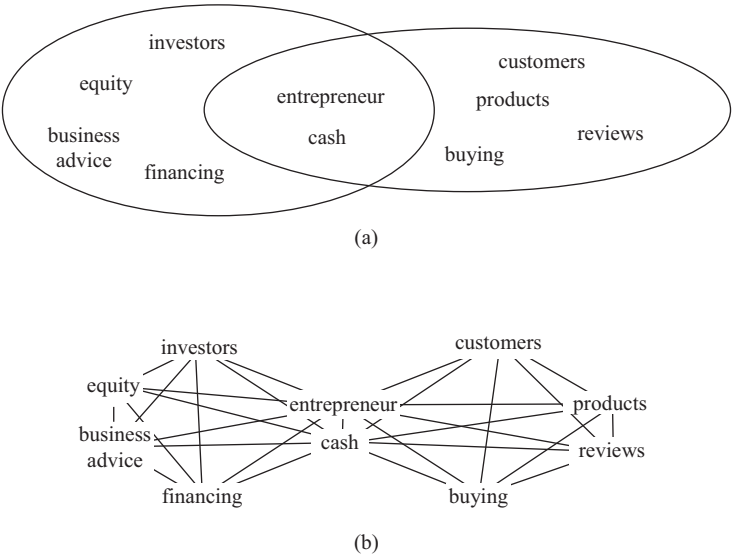

Figure 4: (a) Configuration theory perspective (simplified example visualized as a Venn diagram) (b) Configuration theory perspective (simplified example visualized as polyhedra)

methods are appropriate if the entire configuration can be described by a single set of elements that are tightly interdependent. Networks, however, consist of multiple sets of actors and relationships, which may not all interact directly, and thus limiting the utility of standard set-theoretic methods.

Overall, we find that Håkansson's (1989) conceptual model, the configuration theory perspective, and set-theoretic methods are well suited to studying networks as multiple overlapping sets of interacting elements. Methodologically we reach beyond standard set-theory methods, and introduce the Q-Analysis method (Atkin 1974), also a set-theoretical method, and demonstrate its application to network multiplexity research.

3 The Q-analysis method

Set-theoretic methods have been proposed to study organizational configurations and enable systematic and repeatable description of complex organizational forms, including comparison of these descriptions across cases for cross-sectional or inter-temporal comparison. However, standard set-theoretic methods reduce

these organizations to a single set of interrelated elements (Ragin 2000; Fiss 2007; 2011). We propose using the Q-analysis method – also a set-theoretic method[1] – to study entrepreneurial networks as multiple layers of overlapping sets of elements (e.g., one set for each relationship or type of relationship in the network). The philosophical orientation of Q-analysis is to offer a mathematical language for inductive analysis of the interdependence between a system's structure (referred to as the "backcloth") and its flows (referred to as the "traffic") (Atkin 1974; Gould 1980; Casti 1989), while preserving the identities of individual elements in the system. As an inductive methodology, it is not meant to test theory, but to help researchers develop and refine theory from complex qualitative data. In comparison to more qualitative or interpretive inductive methods, Q-analysis is designed for systematic and repeatable comparison of multiple configurations. For readers who are more interested in the replicability of the method, we recommend a three-part series by Johnson (1990a, 1990b, 1990c), in which he investigates whether "Q-analysis is sufficiently replicable and procedural to be called a methodology" (Johnson 1990c, 475).

Adoption of a configuration theoretical perspective does not necessitate set-theoretical methods. Mixed-methods approaches (Coviello 2005; Jack 2010; Shipilov 2012) may be more appropriate than using a single integrated method if the research question requires capturing cognitive or perceptual factors, or other factors that cannot easily be expressed in terms of actor–resource–activity element combinations, such as trust, governance, affect, or emotional intensity. Interpretive methods may also be more appropriate when there are fewer case studies to compare and each case has fewer elements. However, in using qualitative methods, it may be quite onerous to concisely describe the complexity of organizational forms with any degree of repeatable accuracy and may require more substantive knowledge of the phenomenon.

The Q-analysis method has been used to study structure and flows in a diverse range of systems including human–database interaction (Jacobson, Fusani, and Yan 1993), television network programming (Gould, Johnson, and Chapman 1984; Jacobson and Yan 1998), urban planning (Atkin, Johnson, and Mancini 1971), farming practices and regional development (Gaspar and Gould 1981), organizational configurations (Atkin 1980; Rakotobe-Joel, McCarthy, and Tranfield 2003), and social networks (Freeman 1980; Doreian 1981; Spooner and Batty 1981), including the evolution of social networks (Doreian 1979, 1986). Applied to entrepreneurial networks, Q-analysis involves analysis of multiple

1 Q-analysis (Atkin 1974) is different and unrelated to similarly named methods such as Q-techniques (Miller 1978) and Q-analyses (Blackburn 1982), which are both multivariate data reduction methods.

layers of overlapping sets of network elements (i.e., actors, resources, and activities) to systematically identify, describe, and compare coherent networks. These descriptions concisely summarize which network elements interact and the degree to which these interactions form hierarchical groupings. These hierarchical groupings provide a basis for researchers to contrast and compare networks and formulate preliminary hypotheses. Q-analysis also offers some vector measures to evaluate the complexity of networks in more aggregate form. The steps involved in Q-analysis are laid out as a Roadmap in Figure 5 and described in greater detail below. Following the structure of other methodological papers (e.g., Siggelkow 2002; Fiss 2007; Crawford 2009), we demonstrate the mechanics of the method on a simplified hypothetical illustrative entrepreneurial example, followed by an application to a more detailed yet still illustrative example from case study data.

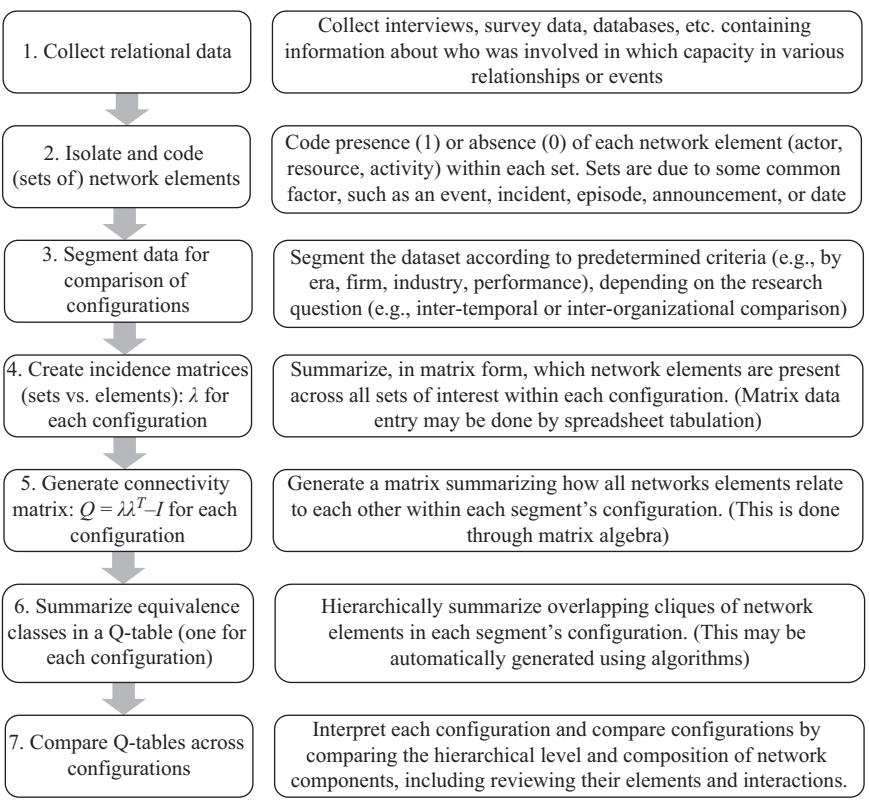

Figure 5: Roadmap for Q-analysis

3.1 Data collection

Data on the elements and sets that compose entrepreneurial networks may be collected in the form of qualitative or quantitative sources. Qualitative data sources include "texts" (Corbin and Strauss 1990; Ryan and Bernard 2003), with each text defining the boundaries of each sub-set of network elements. For example, texts may include individual press releases about strategic alliances (e.g., extracted from ReCap, BioScan, or SDC databases), with each strategic alliance announcement being coded for the various actors, resources, and activities that are involved. Need be, coding would include the date of the press release for later segmentation for inter-temporal or longitudinal comparison. Texts might also be the researcher's own observations from experiments, as done in Jacobson et al.'s (Jacobson, Fusani, and Yan 1993) Q-analysis of structured interviews of users' interactions with a database, wherein each observation record contained a combination of "traffic" and "backcloth" elements. Data may also be collected from more direct quantitative sources such as name-generator surveys from SNA methods (Wasserman and Faust 1994). These surveys elicit itemized lists of which (present or absent) combinations of elements constitute each relationship and thus do not require additional coding.

To explain the method, we re-use the data from the same simplified example used to illustrate the configuration theory perspective in Section 2.4. In this paper, it is more important to provide illustrative examples that allow readers to readily follow every step in the analysis, than it is to provide a large scale detailed empirical analysis of a phenomenon or derive propositions. In the next major section of the paper, we demonstrate the method by drawing on empirical data from three case study papers about the same firm, from which we extract 14 elements that describe three types of relationships and their evolution over two time periods.

3.2 Coding elements and sets

The next step in the process is to code the source data to identify each of the network elements and their occurrence in sets. Therefore, this step is somewhat interdependent on the research design and data sources and involves some subjectivity or substantive knowledge relevant to the research question. Directly analogous to Fiss' (2007, 2011) repeated caution that the substantive knowledge and theoretical interests of the researcher will guide which sets to

sample across and which elements to include in those sets, Johnson cautions that "information is implicit in the interpreter and does not exist in the data files: the *interpretation depends on the person interpreting and his or her prior knowledge*" (1990b, 278, emphasis original). In order to explain the mechanics of the method and its application for network multiplexity research, we do not require significant subjective knowledge and can use the simplified illustrative data in Figure 4(a). No further coding is required since this figure already clearly identifies which network elements comprise each of the two sets.

To control for subjectivity in the coding process and to attain inter-coder reliability, coding schemes may be compared among researchers on the same project (Jacobson, Fusani, and Yan 1993). Coding may also be an iterative process, in which one begins with a tentative coding scheme, reviews the results, and then decides if the coding scheme requires further revision and iteration (Johnson 1990a, 1990b). If SNA-like name-generator surveys are used, then each actor mentioned in the survey may include questions about resources and activities involved in each relationship, so that both structure and flows are captured by the survey. Alternatively, using the same name-generator survey methods, the resource or activity may be pre-specified, to query for which set of actors they involve (see: Lazega and Pattison 1999 or Cross, Borgatti, and Parker 2001 for rare examples of layering of up to five types of communication flows within organizations).

In general, elements in each set need not be exclusive to that set; set overlap is, after all, a central feature of the Q-analysis method. However, each element and set should be distinct (Johnson 1990b, 1990c). For example, if one were to draw on the BioScan Directory as a data source, one could treat each strategic alliance or merger announcement as a distinct set, and code for which firms (actors) were involved, and code-specific products, IP or other key resources mentioned, including coding each activity involved. In comparison, if one were to draw on USPTO data, then resource and activity elements may be limited to just "patents" and "patenting", while each patent may be coded according to the inventor and assignee names (actors) mentioned on each patent.

Further nuances exist in determining the degree to which network elements occur in each set: researchers must decide between a crisp or fuzzy set approach (Ragin 2000; Fiss 2007, 2011). In all examples in this paper, we use crisp sets, with the binary value "1" to indicate that a network element is related to the other network elements in the same set, and the value "0" to indicate when a network element is not part of that set. Fuzzy sets, on the other hand, use threshold measures to specify the extent to which each element occurs in each

set (Ragin 2000; Fiss 2007, 2011). In the Q-analysis terminology, this threshold is called the slicing parameter (Atkin 1974; Johnson 1981).

3.3 Dataset segmentation

As demonstrated by Siggelkow (2002), there is value in describing individual configurations; more so, in describing and comparing multiple configurations, and exploring research questions regarding their variation (relative), performance, and evolution. Q-analysis lends itself to descriptive research about individual configurations, as well as to systematic comparative analysis of groups of similar configurations. Comparative analysis requires segmentation of the dataset and is, in principal, similar to Qualitative Comparative Analysis (QCA) (Fiss 2007, 2011), which uses standard set-theoretic methods.

Segmentation of the dataset should be aligned with the focus of the study. For descriptive or cross-sectional studies, the dataset may be segmented based on specific elements within the dataset (e.g., Gaspar and Gould 1981). For inter-temporal or longitudinal studies, the dataset may be segmented into individual periods or eras (e.g., Siggelkow 2002). To control for relationship decay rates, multiple eras may be combined using "sliding" or "expanding" windows (Doreian 1979, 1986) to analyze fixed duration or cumulative duration time-spans, respectively. For causal inquiry, one might segment the dataset based on a dependent variable (e.g., Jacobson, Fusani, and Yan 1993). In our explanation of Q-analysis (Section 3), we will perform descriptive Q-analysis on only the simplified illustrative configuration. This is followed by our demonstration of Q-analysis (Section 4), including inter-temporal comparison to describe the evolution of an illustrative case study from the literature.

3.4 The incidence matrix (λ)

Each data segment is summarized in an incidence matrix, λ, which identifies which network elements (m rows) occur in which sets (n columns). In our descriptive analysis of the simplified example, we only have one incidence matrix with two sets of elements (2 columns): one representing the *financing* relationships and the other representing the *selling* relationships. These types of relationships are represented in the columns in the incidence matrix shown in Table 1. We have deliberately arranged the elements (rows) and color-coded the sets such that the co-occurrence of the *entrepreneur* and *cash* elements across

Table 1: Incidence matrix (simplified example)

	financing	selling	← Set (by Type of Relationship) Elements:
	1	0	business advice
	1	0	investors
	1	0	financing
	1	0	equity
	1	1	entrepreneur
$\lambda =$	1	1	cash
	0	1	products
	0	1	reviews
	0	1	customers
	0	1	buying

both sets is more obvious. Mathematically, the order of the rows or columns does not actually matter.

The incidence matrix is an input to Q-analysis and not meant to be interpreted, per se. However, for small matrices like the one in Table 1, it may already be possible to interpret the matrix regarding interactions of elements within and across sets (i.e., dyadic and network multiplexity), especially if the elements and sets are neatly arranged and color-coded, as above. For instance, the *financing* relationships (left column) show three flow elements that interact within those relationships: *business advice*, *equity*, and *cash*. Similarly, reviewing the rows reveals one flow element that interacts across types of relationships: *cash*. Due to these interactions, we can deduce that changes in *equity* may trigger changes in *cash* within the *financing* relationships, which may in turn affect *cash* flows in the *selling* relationships and thus also change the need to sell *products*. Structurally, because the *entrepreneur* is the only actor occurring across both columns, we can deduce that they are the main person to coordinate these network multiplexity effects. In Q-analysis terms, such changes in flows are "transmitted" (Johnson 1990a) throughout the system, because only some elements directly interact within or across relationships, but cause other elements to indirectly interact throughout the network. While such interactions within and across relationships (i.e., dyadic and network multiplexity) are visually evident in such a simple, color-coded, and well-organized incidence matrix, they are usually not brought to light until Step 6.

3.5 The connectivity matrix (Q-matrix)

To systematically analyze how *all* the elements in the network directly and indirectly interact, this step involves converting the m by n incidence matrix (λ) into an m by m connectivity matrix, or Q-matrix. This matrix summarizes the interactions between *all* elements and is analogous to "influence matrices" in complex systems analysis (Rivkin and Siggelkow 2003). The connectivity matrix is calculated as $Q = \lambda\lambda^T - M$, where M is an m by m matrix with 1s in every cell.[2]

The values in the connectivity matrix provide two key pieces of information with which to systematically generate and summarize hierarchical groupings of interacting elements (as done the next step in the analysis). First, the values on the main diagonal indicate the *dimension levels* (or *q-levels*) of each element and may be used as a measure of element core-ness (Siggelkow 2002). These values indicate the number of additional sets that each element occurs across, other than the first set in which it appears. For instance, a value of zero indicates occurrence in a single set, with no overlapping sets.

Second, the values in the off-diagonal cells represent the dimension levels of the interaction between any two elements. These values indicate how many sets a given element-pair has in common (minus one). A zero in the off-diagonal cell of the connectivity matrix indicates that the two elements co-occur and interact in only one set. If no interaction occurs between a pair of network elements, this is indicated by a "–" in the appropriate cell in the connectivity matrix.

Like the incidence matrix, the connectivity matrix only represents an intermediate step in the Q-analysis and is also not meant to be interpreted, per se. Nonetheless, it may also reveal network multiplexity patterns, especially if the elements and sets are neatly arranged and color-coded, as in the connectivity matrix for simplified example (Table 2). As before, the elements that directly interact within the *financing* relationships (q-level 0) are shaded yellow, and the elements that directly interact within the *buying* relationships (q-level 0) are shaded blue. Additionally, the two elements that directly interact across both types of relationships (*cash* and *entrepreneur*) are shaded green (q-level 1). Through this direct interaction across both types of relationship, all the other elements indirectly interact.

2 This algebraic data transformation is virtually identical to the matrix algebra used in 2-mode SNA (Faust 1997; Borgatti and Everett 1997; Borgatti 2009), with the additional step of subtracting 1 from the value in every cell. Q-analysis is different from 2-mode SNA in that SNA is focused on the structure and does not integrate the flow perspective.

Table 2: Connectivity matrix (simplified example)

business advice	investors	financing	equity	entrepreneur	cash	products	reviews	customers	buying	
0	0	0	0	0	0	-	-	-	-	business advice
	0	0	0	0	0	-	-	-	-	investors
		0	0	0	0	-	-	-	-	financing
			0	0	0	-	-	-	-	equity
				1	1	0	0	0	0	entrepreneur
					1	0	0	0	0	cash
						0	0	0	0	products
							0	0	0	reviews
								0	0	customers
									0	buying

3.6 Equivalence classes and the Q-table

The final computational step in Q-analysis is to identify equivalence classes.[3] Equivalence classes summarize how elements group together into network components at a given dimension level. Each equivalence class represents a mutually exclusive set of network elements in which all the elements *directly* or *indirectly* interact with all other elements in the same equivalence class, according to the dimension level of their interaction in the connectivity matrix. Consistent with Siggelkow's (2002) notion of core-ness, equivalence classes form the core components of the overall network, and the elements that bring sub-components together are themselves more core than the other elements in the same component. For example, a core actor (e.g., the entrepreneur or a key investor) may bring a portion of the network together. Similarly, it may be a core resource or activity that brings together a portion of the people in the network. Lastly, it may even be a combination of equally core actors, resources, and activities that brings other sub-components together to form network components.

3 Equivalence classes are distinct from structural equivalence (Burt 1987), which occurs when any two actors are connected to all other actors in the rest of the network in the same way.

Sub-components consist of elements that *all directly* interact with each other to form "cliques" (Luce and Perry 1949; Knoke and Kuklinski 1982). The term clique denotes a set of actors who are all interconnected and may be generalized here to denote a set of elements that all interact. A change in one element directly affects all other elements in the same clique. When multiple cliques partially overlap and are brought together via common elements, these cliques form a q-chain. Each equivalence class consists of one q-chain, consisting of one or more cliques. Due to the overlapping elements that chain cliques together, the other elements in those cliques *all indirectly* interact, and changes may propagate throughout the equivalence class via the overlapping elements.

Equivalence classes occur at each dimension level at which elements and their interactions exist and are tabulated by dimension level in what is called the Q-table. At higher dimension levels, there are likely to be fewer elements that interact and form smaller overlapping cliques and equivalence classes, eventually encompassing only the most core elements and interactions.[4] At lower dimension levels, these equivalence classes may begin to merge into larger equivalence classes, eventually encompassing all the elements in the network into a single equivalence class.

For each dimension level (i.e., each row in the Q-table), the mutually exclusive sets of elements that comprise each equivalence class are contained within curly brackets – {}. More detailed Q-tables also summarize each clique within each equivalence class, contained within angle brackets – < > (Johnson 1990a). Higher dimensional equivalence classes indicate that changes may propagate faster and further, since the elements in the equivalence class co-occur with more other elements. The occurrence of multiple equivalence classes at any given dimension level indicates fragmentation into multiple network components.[5] Equivalence classes with few large cliques indicate a higher degree of dyadic multiplexity.[6] In contrast, equivalence classes with many (smaller) cliques indicate a higher degree of network multiplexity.

4 Q-analysis also includes an "eccentricity" measure at the element level, which describes the degree to which an element is more core than the next element to which it is connected (Casti 1989). Eccentricity values of zero indicate structural equivalence of a given element with the other elements to which it is connected. Non-zero values indicate that the element causes overlap of multiple cliques (i.e., the element causes network multiplexity).

5 Mathematically, the maximum number of equivalence classes is equal to the number of sets (columns) in the incidence matrix and would occur if there were no overlap across any sets, i.e., flows and actors are completely independent across relationships.

6 The maximum size equivalence class in terms of elements, is equal to the number of elements (rows) in the incidence matrix, and would occur if all elements occurred within at least one set.

Assembling elements into equivalence classes to summarize them in the Q-table usually begins by reviewing the connectivity matrix (Table 2) for elements that interact at the highest available dimension level. For our simplified example, we have already foreshadowed that the highest value is 1, at which the *entrepreneur–cash* clique exists, followed by the two overlapping cliques at dimension level 0. Scanning the cells of Table 2 for 1s (shaded in green), we indeed see that the *entrepreneur* and *cash* elements directly interact and thus form a clique at this dimension level. Since no other elements or interactions occur at this dimension level, it is the only clique and also the only equivalence class at dimension level 1. Performing the same scan at dimension level 0 (and higher), we see that there are two overlapping cliques, with each clique representing the *financing* relationships (highlighted by the yellow and green shaded cells) or the *buying* relationships (highlighted by the blue and green shaded cells), and the overlap occurring due to the *entrepreneur*, and *cash* elements. As a result of this overlap, the non-overlapping elements in both the cliques all indirectly interact, and these two cliques form a single equivalence class at dimension level 0. Since no other elements occur in the network, this is the only equivalence class at dimension level 0.

The equivalence classes, their level, and composition for this simplified example are summarized in the Q-table below (Table 3). As foreshadowed due to the arrangement and color-coding of the cells in the incidence and connectivity matrices, the Q-table uses the elements' identities to spell out how changes in the flow of *equity* and *advice* from *investors* affect the *cash* available to the *entrepreneur*, which in turn affects the need to generate *cash* by *selling products* according to the *reviews* from *customers*. As stylized here, the indirect interactions enable changes in flows to propagate throughout the entire network, with the changes being propagated via the *cash* and *entrepreneur* elements.

Table 3: Q-table (simplified example)

q-level	Q	Q^*	Equivalence classes
1	1	0	{<entrepreneur, cash>}
0	1	0	{<business advice, investors, financing, equity, entrepreneur, cash>, <entrepreneur, cash, products, reviews, customers, buying>}

The second and third columns of Q-table contain two vectors that describe the fragmentation of the network structure across all dimension levels. The first vector, the structure vector (Q), is a count of how many equivalence classes (i.e., mutually exclusive components) there are at each dimensional level. Network

fragmentation is associated with communication failures (Gargiulo and Benassi 2000), strategies to control flows (Emerson 1962; Burt 1992), and differences in overall network performance (Labianca and Brass 2006; Oh, Labianca, and Chung 2006). The second vector is the obstruction vector (Q^*), which is a variation of the structure vector, in that it counts the number of obstructions between the equivalence classes at each dimension level. The obstruction vector is calculated by simply subtracting the unit value 1 from the structure vector at each dimension level. Flows cannot propagate between components at the dimension level because of obstructions, called q-holes, which are conceptually analogous to structural holes (Burt 1992), but more specific about which dimension level they occur at. The Q-table for the simplified example (Table 3) has a structure vector consisting entirely of 1s, indicating that the network is cohesive and not fragmented at any level, i.e., the flows are interdependent throughout the entire network. Overall, Q-tables are hierarchical summaries of interacting elements and identify precisely which elements are the sources of network multiplexity across a range of (dimension or core-ness) levels for the entire configuration. These summaries then form the basis for comparison of configurations, as explained in the next step.

On a practical note, Q-tables may be constructed systematically using an iterative approach and assisted by computer algorithms. For every dimension level, the values in a diagonal cells are reviewed to identify elements at or above the given dimension level. Starting with these elements, further investigation of the off-diagonal cells is required as to which other elements they interact with at that same level (or higher). This usually requires an iterative search for all possible combinations of cliques and equivalence classes, which may be automated using clique-listing algorithms (e.g., Bron and Kerbosch 1973; Pardalos and Rogers 1992; Harley 2004). Such algorithms save significant time when analyzing larger datasets[7] and are limited only by the researcher's ability to collect and code data and by the computational power to manipulate the matrices and produce the summary tables.[8] We believe Q-analyses of larger datasets and more complex configurations have remained rare because the mechanics of the method are not well articulated and because algorithms for Q-analysis are not broadly accessible beyond those written in outdated programming languages (e.g., Mullins 1976 or Tutzauer 1993).

7 The authors may be contacted for their Q-analysis algorithm for Visual Basic in Microsoft Excel™.

8 The computational resource requirements increase geometrically with the number of elements involved.

3.7 Comparison of Q-tables

A key strength of Q-analysis is the way in which Q-tables provide structured descriptions of configurations, their components, and elements, while preserving the qualitative labels of all the elements. These rich descriptions may be used to contrast and compare cases in a cross-sectional manner, or longitudinally across time periods. As the number of elements and interactions increase (e.g., as with larger datasets and segments containing multiple cases), so does the maximum dimension level in each Q-table. To make Q-tables with different maximum dimension levels comparable, the dimension levels may be normalized by the maximum dimension level of each Q-table. This normalization then expresses the dimension level (e.g., core-ness) of each element, clique, or equivalence class in relative terms (Doreian 1979). See Gaspar and Gould (1981) for an excellent example of relative dimension levels, i.e., q_{rel}-levels.

The simplified illustrative example is a single network and thus does not present an opportunity to compare multiple Q-tables. However, in the demonstration below, we will construct and compare two Q-tables, one for each of two time periods in the evolution of a single firm's network.

4 A Q-analysis of Cambridge Display Technologies

Now that we have explained the mechanics of the Q-analysis method using a simplified illustrative example, we demonstrate the method using the Cambridge Display Technologies (CDT) case study (Maine and Garnsey 2006, 2007; Minshall, Seldon, and Probert 2007). The CDT case allows us to explore how network multiplexity plays a role in their network over two time periods. For this case, the appropriate level of analysis to study network multiplexity is at the level of the entrepreneurial ego-network as represented by multiple simultaneous key relationships, as also recently suggested by Shipilov (2012).

We use the CDT case to demonstrate the Q-analysis method for a number of reasons. First, CDT is interesting because it is an advanced materials venture. This is a sector known for complex commercialization processes which are contingent on mobilization of investors and strategic partners (Maine and Garnsey 2006, 2007). Second, CDT's story involves a critical event in 2000 that caused a significant change in commercialization strategy and network. This (acquisition) event creates an opportunity to investigate the role of network multiplexity for both time periods and its role in the transformation. Third, the available case study data were sufficiently detailed to be able to identify

individual actors, resources and activities, and their interactions. These articles should also be readily available to most readers of this article, thus enabling reconstruction of the present data and analysis from the source data, should readers choose to do so. Lastly, on an andragogical note, the available data are complex enough to show interactions within and across relationships, and thus suited to studying network multiplexity, but simple enough to follow the mechanics without hiding behind computer algorithms. We note here that there is significant potential for the proposed method in analyzing larger and more complex datasets, as done by Gaspar and Gould (1981), Gould, Johnson, and Chapman (1984), or Jacobson, Fusani, and Yan (1993).

4.1 Data collection

Data about CDTs alliance portfolio pre- and post-acquisition in 2000 are from Maine and Garnsey (2006, 2007) and Minshall, Seldon, and Probert (2007). These three articles comprehensively describe the evolution of both CDT and their entrepreneurial network.

4.2 Coding elements and sets

To maintain focus on demonstrating the method, we aggregate individual relationships up to three stylized types of relationships – financing, licensing, and manufacturing – as shown in Tables 4 and 5. Each type of relationship involves a different set of multiple resources and activities. A more detailed analysis of this case study may have included naming each actor (including individual investors, licensees, and manufacturers), finer temporal segmentation (by year), more specificity about resources (including individual patents, specific materials, or payments), and provided finer granularity of activities (including specific steps in the process of licensing, manufacturing or financing, such as bidding, negotiating, exchanging, maintaining, or dissolving).

Table 4: Types of relationships for CDT (1998–2000 segment)

Structure elements	**Flow elements**	
Type of relationship: actors	**Types of resources**	**Types of activities**
Financing: CDT & investors (e.g., CRIL, University, Genesis and Intel)	Equity, cash, reputation,	Financing
Licensing: CDT & licensees (e.g., Philips, Hoechst, Uniax, SEC, and HP)	IP, cash, materials, reputation	Licensing

Table 5: Types of relationships for CDT (2001–2002 segment)

Structure elements	Flow elements	
Type of relationship: actors	**Types of resources**	**Types of activities**
Financing: CDT & investors (e.g., CRIL, University, Genesis, Intel, Kelso, and Hillman)	Equity, cash, reputation, advice	Financing
Licensing: CDT & licensees (e.g., Philips, Hoechst, Uniax, SEC, HP, and 12 more)	IP, cash, materials, reputation	Licensing
Manufacturing: CDT & manufacturers (e.g., Philips, MDC, Litrex, Opsys, and Osram)	IP, cash, products, materials	Manufacturing

4.3 Dataset segmentation

In order to demonstrate the method's use for studying network evolution, we segment the data into two time periods: pre- or post-acquisition. The acquisition event in 2000 marked a significant transition in available resources and network configuration. Prior to the acquisition, CDT had four investors and five licensees and was struggling to prove the viability of their IP and materials to the licensees. After the acquisition (by Kelso and Hillman), the number of investors increased to six, and the number of licensees increased to seventeen. Importantly, the additional capital enabled adopting a manufacturing strategy by adding five manufacturers to the network, including their own.

4.4 Incidence matrices

Using the data in Tables 4 and 5, we create incidence matrices (λ) with the rows made up by the four actor elements (i.e., *investors*, *licensees*, *manufacturers*, and the *entrepreneur*), seven resource elements (*equity*, *cash*, *reputation*, *IP*, *materials*, *products*, and *advice*) and three activity elements (*financing*, *licensing*, and *manufacturing*). The columns in the incidence matrix represent the types of relationships (*licensing*, *financing*, and *manufacturing*).[9] To make the matrices visually easier to compare across both time periods, we make them the same dimensions by including all three types of relationships, as depicted in Tables 6 and 7, respectively. Adding a column of zeros for the *manufacturing* relationships in the

9 Labels of the types of relationships represent their *main* purpose (Lechner, Dowling, and Welpe 2006), while acknowledging that each relationship actually involves more than a single benefit, resource, or activity.

Table 6: CDT incidence matrix (1998–2000 segment)

$$\lambda = \begin{array}{c} \begin{array}{ccc} \text{financing} & \text{licensing} & \text{manufacturing} \end{array} \\ \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \end{array} \begin{array}{l} \leftarrow \textbf{Set (by Type of Relationship)} \\ \\ \textbf{Elements:} \\ \text{entrepreneur} \\ \text{investors} \\ \text{equity} \\ \text{financing} \\ \text{cash} \\ \text{reputation} \\ \text{licensees} \\ \text{licensing} \\ \text{IP} \\ \text{materials} \\ \text{advice} \\ \text{manufacturers} \\ \text{products} \\ \text{manufacturing} \end{array}$$

Table 7: CDT incidence matrix (2001–2002 segment)

$$\lambda = \begin{array}{c} \begin{array}{ccc} \text{financing} & \text{licensing} & \text{manufacturing} \end{array} \\ \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \end{array} \begin{array}{l} \leftarrow \textbf{Set (by Type of Relationship)} \\ \\ \textbf{Elements:} \\ \text{entrepreneur} \\ \text{investors} \\ \text{equity} \\ \text{financing} \\ \text{cash} \\ \text{reputation} \\ \text{licensees} \\ \text{licensing} \\ \text{IP} \\ \text{materials} \\ \text{advice} \\ \text{manufacturers} \\ \text{products} \\ \text{manufacturing} \end{array}$$

pre-acquisition incidence matrix has no impact on the mathematical transformations or results.

4.5 Connectivity matrices

We then calculate the connectivity matrices: $Q = \lambda\lambda^T - M$. The diagonal cells in the connectivity matrix in the first time period (Table 8) reveal that the *entrepreneur*, *cash*, and *reputation* elements each overlap two sets (their dimension levels are 1) and thus contribute to network multiplexity. Meanwhile, the *investors*, *licensees*, *equity*, *IP*, *materials*, *financing*, and *licensing* elements are only present in one set each (their dimension levels are 0) and thus mainly contribute to dyadic multiplexity. The remaining elements are not yet present in this network, as represented by the "–"s. The resulting connectivity matrix for the second time period (Table 9) reveals the inclusion of the remaining elements (fewer "–"s), and the increase in interactions between elements (increases in off-diagonal cell values).

Table 8: CDT connectivity matrix (1998–2000 segment)

	entrepreneur	investors	equity	financing	cash	reputation	licensees	licensing	IP	materials	advice	manufacturers	products	manufacturing
entrepreneur	1	0	0	0	1	1	0	0	0	0	-	-	-	-
investors		0	0	0	0	0	-	-	-	-	-	-	-	-
equity			0	0	0	0	-	-	-	-	-	-	-	-
financing				0	0	0	-	-	-	-	-	-	-	-
cash					1	1	0	0	0	0	-	-	-	-
reputation						1	0	0	0	0	-	-	-	-
licensees							0	0	0	0	-	-	-	-
licensing								0	0	0	-	-	-	-
IP									0	0	-	-	-	-
materials										0	-	-	-	-
advice											-	-	-	-
manufacturers												-	-	-
products													-	-
manufacturing														-

Table 9: CDT connectivity matrix (2001–2002 segment)

	entrepreneur	investors	equity	financing	cash	reputation	licensees	licensing	IP	materials	advice	manufacturers	products	manufacturing
entrepreneur	2	0	0	0	2	1	0	0	1	1	0	0	0	0
investors		0	0	0	0	0	-	-	-	-	0	-	-	-
equity			0	0	0	0	-	-	-	-	0	-	-	-
financing				0	0	0	-	-	-	-	0	-	-	-
cash					2	1	0	0	1	1	0	0	0	0
reputation						1	0	0	0	0	0	-	-	-
licensees							0	0	0	0	-	-	-	-
licensing								0	0	0	-	-	-	-
IP									1	1	-	0	0	0
materials										1	-	0	0	0
advice											0	-	-	-
manufacturers												0	0	0
products													0	0
manufacturing														0

4.6 Equivalence classes and Q-tables

For both time periods, the off-diagonal cells in each connectivity matrix (Tables 8 and 9) are reviewed to form equivalence classes at each dimension level, starting with the highest level. For the pre-acquisition period, we scan the cells of Table 6 for 1s (highlighted in green) and see that the *entrepreneur*, *cash*, and *reputation* elements form a clique at this dimension level. It is also the only clique at dimension level 1, and thus forms the sole equivalence class at this level, as summarized in the first row of the Q-table (Table 10). This equivalence class has implications for how CDT manages their relationships: partners in any one relationship may be willing to risk their *cash* and *reputation* because they see that the *cash* and *reputation* in another (type of) relationship is commensurate with theirs.

Repeating this scan for interacting elements at dimension level 0 (or greater), we see two overlapping cliques at this dimension level: one representing the *licensing* relationships (highlighted by the yellow and green shaded cells) and the other representing the *financing* relationships (highlighted by the blue and green shaded cells). The overlap occurs due to the *entrepreneur*, *cash*, and *reputation* elements (repeated across both cliques and highlighted by the green shaded cells). As a result of this overlap, these two cliques chain together to

Table 10: CDT Q-table (1998–2000 segment)

q-level	Q	Q*	Equivalence classes
1	1	0	{<entrepreneur, cash, reputation>}
0	1	0	{<entrepreneur, investors, equity, cash, reputation, financing>, <entrepreneur, licensees, cash, reputation, IP, materials, licensing>}

form one equivalence class. It is also the only equivalence class at dimension level 0, as summarized in the second row in the Q-table (Table 10). This equivalence class provides greater detail regarding the how CDT manages their relationships. Changes in the flow of *materials* and *IP* in the *licensing* relationships may directly cause changes in the flows of *cash* and *reputation* in the same type of relationship. These changes then affect the *cash* and *reputation* flows in the *financing* relationships, and thus also affect how *investors* value their *equity* positions in CDT. Such interactions within and across relationships reveal network multiplexity processes that are often overlooked in network research (Shipilov 2012) and can inform entrepreneurs about how to manage the function and evolution of their networks.

4.7 Comparison of Q-tables

In comparing CDT's Q-tables across both time periods (Tables 10 vs. 11), we see that the network is more multiplex in the second time period, driving the need for more complex stakeholder and flow management by the entrepreneur. The increase in network multiplexity is evident in (i) the higher maximum dimension level (from 1 to 2), (ii) the larger equivalence classes, and (iii) the increase in the number of cliques and elements per equivalence class.

Table 11: CDT Q-table (2001–2002 segment)

q-level	Q	Q*	Equivalence classes
2	1	0	{<entrepreneur, cash>}
1	1	0	{<entrepreneur, cash, reputation>, <entrepreneur, cash, IP, materials>}
0	1	0	{<entrepreneur, investors, equity, cash, reputation, advice, financing>, <entrepreneur, licensees, cash, reputation, IP, materials, licensing>, <entrepreneur, manufacturers, cash, IP, materials, products, manufacturing>}

The labels of the elements in the Q-tables enable us to describe the increase in network multiplexity in qualitative terms. The acquisition included *advice* in the *financing* relationships, and the addition of the *manufacturing* relationships. More specifically, the *manufacturing* relationships included *IP* and *materials* flows which interacted with the *licensing* relationships. The *manufacturing* relationships also contributed to an increase in the importance of *cash* flows across all relationships.

5 Discussion

We acknowledge that learning a new method may be daunting. In this explanation and demonstration of the Q-analysis method, we have drawn parallels to other methods with which many readers will already be familiar. The most significant effort required with this method should be in collecting the data and interpreting the results, since software algorithms, once developed, can be used to manipulate the matrices and automatically produce the Q-tables. We posit that the real value of the Q-analysis method is in concisely describing and analyzing massively complex systems, as exemplified by Gaspar and Gould (1981), Gould, Johnson, and Chapman (1984), or Jacobson, Fusani, and Yan (1993). For this paper, we felt that analysis of a larger dataset and use of a software algorithm would distract from explanation of the method and be too complicated to follow as a demonstration of the method.

The proposed integrated approach provides theory development opportunities regarding network multiplexity and evolution. While network multiplexity research is lacking in management (Shipilov 2012) and many other fields (Johnson 1990b), it is especially important to entrepreneurship when one considers that the essence of entrepreneurship is carrying out new combinations (Schumpeter 1934) of elements that are predominantly external to the venture. We thus see a key research opportunity in the identification of entrepreneurial network configurations which are described by both structure and flow conditions. These descriptions may extend research on entrepreneurial network composition (Lechner and Dowling 2003; Lechner, Dowling, and Welpe 2006) by being more precise about interactions within and across relationships. The Q-tables spell out the dyadic and network multiplexity in qualitative detail in the form of the hierarchically organized equivalence classes, containing cliques and elements. They also provide some quantitative measures of multiplexity in terms of the count, dimension level, and size of each equivalence class and clique. The proposed integrated approach thus provides a finer-grained analysis

of exactly which elements cause network multiplexity, which therefore enables development of more accurate theory regarding outcomes, capabilities, or other factors that are affected by network multiplexity.

We also see research opportunities in the area of entrepreneurial network evolution. Building on the above discussion about how network multiplexity affects how networks function, and acknowledging that entrepreneurial networks are particularly dynamic (e.g., Elfring and Hulsink 2007; Jack, Dodd, and Anderson 2008; Jack et al. 2010), it is practically essential to consider network multiplexity when exploring entrepreneurial network change. By comparing multiple Q-tables, each representing a different time period, we can begin to understand how network multiplexity changes over time and can infer how changes propagate across relationships and affect performance.

While an integrated approach has many merits (see also: Hoang and Antoncic 2003; Jack 2010; Slotte-Kock and Coviello 2010), it also has its own limitations. Compared to structure-only approaches, an integrated approach may not have the same level of generality or be as universally portable across populations of organizations or settings. Compared to flow-only approaches, an integrated approach may not capture the same level of detail at the level of the individual actors or relationship, thus potentially omitting attributes of the actors (e.g., capabilities, cognition, or attitudes), and processes or causal mechanisms (Yli-Renko 2005; Vissa 2011). Empirical limitations exist, in that the quality of the analysis is dependent on the quality and completeness of the data. In the above case, we have used secondary data sources that only reveal some of the myriad of connections CDT had in either time period. A systematic approach to collecting primary data at multiple intervals may include modifying name-generator surveys (e.g., Wasserman and Faust 1994) to include resource and activity elements associated with each of the actors. Such (semi-)structured data would then also benefit from more qualitative stories that can elaborate on causal mechanisms at play across time periods.

The proposed approach, and in particular the conceptualization, also has implications for entrepreneurs. By adopting the proposed conceptualization of networks as layers of multiple interrelated resources, entrepreneurs can make more informed decisions about who to connect to. For example, in the illustrative case above, the entrepreneur accepted capital from the acquirer to keep his venture alive. The new capital enabled a dramatic change in the structure of alliances and addition of manufacturing partnerships. However, the acquisition also meant that the founder lost control of ownership and left the venture. With a more nuanced conceptualization and analysis of the interactions of the cash, IP and actors involved, it is entirely conceivable that the entrepreneur may have chosen to pursue a different strategy to sustain their venture without an acquirer.

6 Conclusion

Network-based studies are an important part of entrepreneurship research. However, we argue that prior research on entrepreneurial networks has been limited by applying a structure-only perspective or flow-only perspective, and that these perspectives are individually are unable to analyze network multiplexity and its effect on how networks function and evolve. In response, we introduce an integrated approach for analyzing how structure and flow elements of entrepreneurial networks interact, that is uniquely suited to network multiplexity research.

The integrated approach presented here is built on a new combination of Håkansson's conceptual model, the configuration theory perspective, and Atkin's Q-analysis method. Håkansson's conceptual model is consistent with both structural conceptualizations (e.g., who is connected to whom?) and relational conceptualizations (e.g., how multiplex are individual relationships?). The configurational perspective is also consistent with the structural perspective (e.g., combinations of actors) and the flow perspective (e.g., combinations of resources and activities). Lastly, the Q-analysis method was specifically designed to study the structure ("backcloth") and flows ("traffic") of organizational systems, including entrepreneurial networks. The conceptual model, theoretical perspective and method all complement each other, and require minimal adaptation to the entrepreneurial network context. Because the conceptual model and theoretical perspective are likely to resonate with or even be familiar to entrepreneurial network researchers, our emphasis in this paper is on explaining the component they are likely to be least familiar with: the Q-analysis method. We posit that an integrated approach is an important step toward improving our understanding of network multiplexity and its role in determining how entrepreneurial networks function and evolve. While we have presented arguments and demonstrated the method in the context of entrepreneurship, they also have relevance for other inter- or intra-organizational networks.

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