Interorganizational Network Formation

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June 30, 2023

Abstract

Interorganizational networks are formal or informal relationships between organizations established to share knowledge, resources, and expertise with the intent to create value and, possibly, achieve a common goal. In today's complex business environment, forms of collaboration and relationships, such as joint research and development, supply chains, and social and environmental initiatives, require careful planning and ongoing effort to match the desired targets. Given the inherent complexity of interorganizational networks, the achievement of such objectives also rests on the processes underpinning network formation. In this contribution, we analyze different approaches to network formation, discussing their impact on shaping emerging structures. Finally, we discuss how agent-based models can contribute to the modeling of complex network formation.

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Keywords: Agent-based models; Complexity; Interorganizational networks; Multiplex networks; Network formation.

1 Introduction

In the last two decades, the role of networks in management studies, especially when dealing with organizations, has grown at a furious pace. A recent survey (Moretti, Piccione, and Tolotti 2023) has highlighted the presence of more than 480 papers published in 4-star ABS journals (Walker and Wood 2021) on this topic in the time window from 2002 to 2021. Specifically, in the field of interorganizational studies, the mechanisms under which complex structures emerge, evolve, and stabilize have received increasing attention (Harini and Thomas 2021), together with the discussion on how different network architectures may impact the achievement of goals and objectives stated at the heart of the network creation (e.g., Kim, Funk, and Zaheer 2023).

Several authors helped shed light on the *consequences* of different structures of social networks (e.g., Ahuja, Soda, and Zaheer 2012). However, less attention has been given to the *drivers* of the emergence of such network structures. Studying processes of network formation can instead enrich our understanding of the dynamics of network evolution (Pomeroy et al. 2020) and the final network architectures (Sytch and Tatarynowicz 2014).

In this contribution, we analyze the process of interorganizational network formation, emphasizing different perspectives and dimensions. First of all, we introduce some of the features that characterize interorganizational networks within the management literature, highlighting different viewpoints and approaches. This introductory analysis contributes to uncovering the importance of understanding the nature of emerging networks in the context of interorganizational relationships (Powell, Packalen, and Whittington 2012). Second, we propose a broad categorization of the vast literature on network formation, not only related to organizational networks but rather from a general perspective. We disentangle some distinctive traits related to three different strands of literature on network formation: a mechanical approach; an orchestrated optimization-based approach; and an economic (micro-founded) approach. In doing so, we strive to bring together the insights from different traditions of network studies: network scholars have encouraged the use of model-based theorizing (Borgatti and Halgin 2011), and the complementarity between different approaches has been emphasized by influential scholars: "The analysis of the incentives to form networks and groups and resulting welfare implications [...] is largely complementary to the social networks literature both in its perspective and techniques," (Dutta and Jackson 2003, 2).

Relying on this double-sided perspective, we identify some traits of classical models of network formation that deserve attention. Specifically, complexity such as multiplexity or heterogeneity, together with the absence of perfect knowledge among economic actors, must find space in modeling network formation. To this aim, in the last section of this contribution, we propose a simple mechanism of network formation based on an Agent-Based Model (ABM), inspired by the pioneering work by (Jackson and Wolinsky 1996). We show how introducing heterogeneity and multiplexity may give rise to a variety of interesting network structures.

2 Defining interorganizational networks

Interoroganizational networks are, essentially, social networks whose nodes (actors) are firms or organizations. The relationships among firms and organizations have been a global phenomenon and the object of management scholars' attention for decades (e.g., Grandori and Soda 1995; Parmigiani and Rivera-Santos 2011).

Two different approaches have been used to conceptualize this widespread phenomenon in the management literature. On the one hand, scholars have used the metaphor of the *network as a perspective* to understand and represent relationships among organizations (e.g., Zaheer, Gözübüyük, and Milanov 2010; Borgatti and Halgin 2011). From this viewpoint, the network is a useful metaphor to understand the effects that interorganizational relationships, such as buyer-supplier relationships, strategic alliances, investment bank ties, etc., have on the focal firm or organization. In a nutshell, the idea is that "the pattern or structure of ties among organizations and the tie strength and content have a significant bearing on firm behavior and on important firm outcomes such as performance," (Zaheer, Gözübüyük, and Milanov 2010, 62).

On the other hand, scholars have also embraced a stronger sociological understanding of *networks as organizations* (Kilduff and Tsai 2003; Powell 1990). This notion of networks has a rich tradition in organizational and sociological studies (e.g., Nohria and Eccles 1992). In this approach, the network is defined as "any collection of actors ($N \geq 2$) that pursues repeated, enduring exchange relations with one another and, at the same time, lack a legitimate organizational authority to arbitrate and resolve disputes that might arise during the exchange," (Podolny and Page 1998, 59). In stark contrast to the *network as a perspective* approach, here the focus is on the network as a whole, and the structure of relationships among organizations becomes an aspect to be considered regarding the coordination and governance of the network itself.

These two approaches need not be mutually exclusive: they both analyze systems of relationships as bringing direct and indirect benefits and liabilities to firms or organizations, but they do it for different reasons. The analysis of these relationships can rely on robust network methods (Wasserman and Faust 1994; Thurner, Klimek, and Hanel 2018, Chap. 4) that are able to capture which structural aspects of the network (e.g., centralization, cohesiveness, path length, etc.) relate to specific effects at the firm level (in jargon, *ego*) and the whole network level. For a more extensive discussion on social network analysis, see also Chapter 16 of this volume (Campos 2023) CROSSREF).

The actors of interorganizational networks are *organizations*, firms, or institutions. This key element distinguishes these relationships from *intra*organizational networks, whose nodes are individuals operating in the context of a single firm or organization. The reason for this distinction is that a number of concepts in organization and management theories have different meanings and interpretations in the two domains, i.e., inter- and intra-organizational networks.

The first concept is *trust* as an organizing principle (McEvily, Perrone, and Zaheer 2003). Trust plays a fundamental role in interorganizational relationships because it can act as a coordination device and a means of relational governance (Cao and Lumineau 2015), i.e., "governance [that] emerges from the values and agreed-upon processes found in social relationships" (Poppo and Zenger 2002, 709). However, the literature has clearly stated how trust at interpersonal and interorganizational levels are two distinct – yet related – aspects (Zaheer, McEvily, and Perrone 1998). At the same time, a feature distinguishing intra- and inter-organizational networks is the role of hierarchy: within organizations, clearly defined formal authority relationships overlap with informal links (Zaheer and Soda 2009), whereas establishing relationships across organizational boundaries involves "a voluntary arrangement between independent organizations to share resources," (Ahuja 2000, 426; see also Hidalgo 2011), as well as benefits.

The voluntary dimension of interorganizational relationships and networks relates to mechanisms and drivers of network evolution. For a long time, social network analysis has been accused of lacking a dynamic and time-oriented perspective (Borgatti, Brass, and Halgin 2014), whereas a longitudinal dimension is fundamental to understanding the relationship between network structures and network outcomes (Ahuja, Soda, and Zaheer 2012). In fact, the past structure of interorganizational networks has a profound impact on current and future network architectures (Milanov and Shepherd 2013) and outcomes (Soda, Usai, and Zaheer 2004). For this reason, it is important to observe, represent, and study networks as evolving over time "to predict which networks are likely to form when [nodes] have the discretion to choose their connections," (Jackson 2005, 12).

The evolution of interorganizational networks can follow different paths and trajectories depending on which mechanisms and reasons spur the development of the actual network (e.g., Kilduff and Tsai 2003). Management scholars have characterized networks – and relatedly, network governance – based on the distinction between orchestrated and spontaneous (i.e., emergent) networks (Dagnino, Levanti, and Mocciaro Li Destri 2016; Provan and Kenis 2008) in quite dichotomous terms, even if in empirical reality the distinction is more blurred. On the orchestration side, the "presence of one (or more) organizations ... intentionally influence[s] the changes of the entire network structure," whereas, on the emergent network side, network evolution can derive from "a myriad of intentional actions carried out by network organizations in the pursuit of their individual goals," (Dagnino, Levanti, and Mocciaro Li Destri 2016, 354-356).

Before dealing with network emergence in the next sections, we briefly sketch the characteristics of orchestrated networks. The process of network orchestration has been defined as "assembling and developing an interorganizational network" (Paquin and Howard-Grenville 2013, 1623). It has been the object of considerable attention among management scholars due to the particularly effective process of coordination among organizations. Relatedly, the literature has also developed the concept of *goal-directed networks* (Kilduff and Tsai 2003), suggesting a teleological explanation of the process of network evolution over time. While orchestrated and goal-directed networks might be indistinguishable from an empirical point of view, the theoretical mechanisms explaining them differ. *Orchestration* implies focusing attention on the process, while *goal-directedness* implies paying attention to the desired outcome.

3 Network emergence and network formation

As we indicated in Section 2, interorganizational orchestrated or goal-directed networks usually bring together firms for a specific network purpose. On the other hand, firms can coalesce together while pursuing their individual goals. As already pointed out by Dagnino, Levanti, and Mocciaro Li Destri (2016), this dichotomy between orchestrated and emergent networks has also played a role in the evolution of the literature in network science.

To draw attention to what we believe are some of the main traits of this literature, in this section, we will pursue a historical digression on the theory of network formation developed over the last 25 years or so. We propose a possible (and rough) categorization of the vast literature, identifying three main approaches to the study of networks: the mechanical approach; the optimization-based approach; and the economic approach. This is of course a simplistic partition of this large body of literature, without any claim to be comprehensive and span the entire research in this area. Our intent is to highlight the main patterns of the different strands, and to relate such literature with the world of agent-based models and the theory of organizational networks.

Namatame and Chen (2016) and Newman (2018) acknowledge the famous Watts and Strogatz (1998) paper on small-world networks as the beginning of the modern era of network science; Barabâsi et al. (2002) proposed the scale-free network almost at the same time. When considering such classes of generative models, attention is mainly focused on the statistical properties of the emerging large network, such as degree distribution, clustering, density, etc. As an example, the small-world model has been proven to explain some properties of real networks (see, for example, Davis, Yoo, and Baker 2003; the characteristics of small-world networks have also been used to explore the features of some collaborative settings as in Uzzi and Spiro (2005)).

However, small-world networks did not possess the scale-free properties recognized in many real social networks (see Barabâsi et al. 2002). Analysis in this strand of literature is often related to asymptotic findings, namely, letting the number of nodes be large (as an approximation of an infinite-size network). Moreover, this algorithmic procedure is not guided by any optimization principle. Although some behavioral traits can be associated with the generation of single links, the generative rule in these models is often mechanical, and agents have no objective or willpower.

The essence of these two contributions and many follow-up studies is to propose automatic generation procedures of networks that can be mathematically formalized and that give rise to the emergence of configurations that can be described analytically. We refrain from surveying the most recent developments of this mechanical approach to network emergence; the scope of the present contribution is rather to flesh out the main traits and underlying logic of the three classes of models, and to analyze the merits and limits of mechanical, optimization-based, and economic approaches to network formation.

This rough categorization is not exclusive: some behavioral traits can be attributed to the formation mechanism of preferential attachment. Namatame and Chen (2016) stress that this approach contains some seeds that can be referred to as embryonic features of agent-based models: the probability of a new link at a given node depends on the number of existing links at that node. This imitation rule invokes an entire literature on herding, such as the Schelling (1971) segregation model or the Granovetter (1978) collective behavior model, or the idea of *homophily*. The fact that agents tend to connect more easily with others who have similar traits is commonly accepted (see Lazarsfeld and Merton 1954; Currarini, Jackson, and Pin 2009; McPherson, Smith-Lovin, and Cook 2001; Kilduff and Tsai 2003). In some sense, new links (and nodes) are generated according to some behavioral rules that are economically sensible. However, the boundary between purely statistical mechanisms and behavioral rules underlying an ABM is not completely crisp. For instance, Prietula 2011 discusses the differences and commonalities between networks that emerge from a model of preferential attachment and the ones related to models incorporating specific social behaviors such as homophily.

These reflections enable us to identify a second strand of literature, which we label as optimization-based. In this case, some orchestration is in place to create an optimal network for a specific need; think, for instance, of an efficient transportation network. Notably, the target is macro rather than micro: an exogenous decision maker (*deus ex machina*) aims at maximizing some objective function of the entire network (rather than single participants' satisfaction). For example, Cancho and Solé (2003) propose an algorithm to look for an equilibrium network that aims to minimize link density and/or average distance. Here, the numerical procedure starts with a random network; then, a pair of nodes is randomly selected, to add a new link or dismantle an existing one. Then, the value of the performance of the network before and after the change is evaluated to accept the new structure. The procedure is repeated until a local equilibrium is reached, meaning that there is no space for an increase in the value of the performance through the deletion or addition of single links. The networks generated by the previous procedure are rather diverse: from configurations close to exponential-like networks or scale-free graphs to star-shaped structures.

Newman (2018) likens this literature to procedures called "random hill climbing algorithms" or "greedy algorithms" where autonomous systems look for local equilibria in a performance space (see Yuret and De La Maza 1993). In this respect, this second strand of literature shares some traits with ABMs, although the process guiding the dynamics is more macro than micro. Compared to the first group of papers, this second category makes explicit reference to the idea of optimization and self-organization. The different assumptions and structural properties of the networks deriving from mechanical and optimization approaches mirror the distinction that Dagnino, Levanti, and Mocciaro Li Destri (2016) make around emergent and orchestrated networks. In fact, the optimization approach reflects the perspective of the orchestrator (the *deus ex machina*), while the mechanical approach can better capture the processes of development of emergent networks. However, as we will see in the next paragraphs, both these classes of models fail to completely capture the behavior of economic and social agents.

Beyond the advent of the above-mentioned models, the end of the past century also witnessed the appearance of a third, economically oriented, strand of literature. Here the peculiarity is the definition of a micro-founded mechanism of link generation. The pioneering studies by Jackson and Wolinsky (1996), published before the conventional date of birth of network science in 1998, and Bala and Goyal (2000) focus on the single actor (or on the single tie). The goal is to maximize a private payoff characterized by a benefit in terms of (directed and undirected) connections and by a cost of building and maintaining those connections. Eventually, an equilibrium is reached and it is therefore possible to measure the aggregate cost/benefit associated with the emerging network.[1] In this vein, aggregate welfare and performance can be analyzed.

As Goyal (2016) later noticed, the economic approach is different from the other approaches (such as the classical sociological approach *à la* Granovetter 1978). Here, the focus is on how single economic agents shape the network due to their personal payoffs: the social structure is envisioned and created through individual actions in response to others (as in classical game theory). On the contrary, in previous studies and also in the majority of the papers belonging to the two groups analyzed so far, the rationale is exactly the opposite: how the network influences a single agent's behavior.

At this point, a remark is due. This distinction relates to the management literature on interorganizational networks in two ways. Firstly, it is a meaningful lens to understand the criticism leveled at the network theory for being "all structure, no content" (Borgatti, Brass, and Halgin 2014): the excessive

1. We postpone to the next section a definition of the concepts of "efficient" and "pairwise stable" equilibria.

emphasis on the structure of the network surrounding one organization (the so-called *ego* network) could obscure the individual agency and capabilities of organizational actors. Similarly, mechanical and optimization-based models of network formation emphasize the structure, and give the individual agency a minor conceptual role.

Secondly, as we explained in Section 2, the *network as a perspective* approach focuses on focal organizations and how they develop their ego network: this perspective is naturally closer to the economic approach to network formation. The *network as an organization* approach, conversely, focuses on the whole network, enabling it to be compared more easily to the optimization approach to network modeling. However, we must also note that the *network as an organization* approach focuses on governance and coordination of network relationships: for this reason, it is also important to understand the motives and behaviors of single organizations. The economic approach could therefore be a useful complement for linking micro and macro aspects of network relationships. As we will see in Section 4, ABMs are capable of bridging this micro/macro divide.

Returning to the economic approach, this literature is based primarily on tools from game theory, probability theory, and graph theory. Moreover, unlike the mechanical approach, where emphasis is placed on statistical properties of large networks, in this case the networks under consideration are usually small/medium in size, and the goal is to study in detail both local and global properties (e.g., traits of ego networks, as well as the whole network). As a matter of fact, under some simplifying assumptions, such as symmetry and efficiency, it is shown that there are just a few types of efficient equilibria: empty networks (if costs outweigh benefits), full networks (in the opposite situation), and star-shaped or "wheel" networks. The fact that the spectrum of outcomes is so limited is related to some peculiarities in the structure assumed by the modeler: the information structure and the homogeneity assumption on the types of actors (in relation to costs and benefits). Concerning the former, those approaches are characterized by full rationality and perfect knowledge: agents, when deciding their actions (for example, adding one link to the existing network), possess the ability to anticipate in full the consequence of such actions. More specifically, they perfectly envision the new network and all the network topology properties needed to exactly compute the new benefit structure. The latter assumption, homogeneity, makes all the actors ex-ante identical; this assumption, in conjunction with perfect rationality, calls for an ex-post symmetric structure. In the case of a star-shaped structure, the agent that turns out to be at the core of the network in its infancy, due to the random selection process, plays the role of catalyst for all subsequent emerging links, making the agent the hub of a perfect star.

As stressed by Vega-Redondo (2007), it is rather obvious that both these assumptions are very simplistic and that either noise, heterogeneity, or bounded rationality must be considered to obtain more realistic emerging structures. In recent years, some authors have proposed models that relax those assumptions. For example, Olaizola and Valenciano (2021) consider heterogeneous payoff structures, whereas Song and Schaar (2015) assume bounded rationality. In both papers, one of the main consequences of the relaxation of the hypotheses is the establishment of more complicated (and realistic) coreperiphery network structures: the star-shaped principle is still in place, but now there is a small number of hubs with their local quasi-star networks forming a unique giant component. This happens for values of the cost/benefit structure that are non-extreme; otherwise, the two degenerate situations of full or empty networks continue to emerge. Therefore, either by relaxing the basic assumptions characterizing models of economic theory or by assuming behavioral rules as in the second class of papers described above, the emerging networks are typically hub and spoke, and resemble network structures that are closer to real networks.

Summarizing, we have seen that various approaches to network formation and emergence are possible. All of them share the general intent to explain how networks are formed. However, the mechanisms behind the network formation differ considerably. We have also seen that behavioral rules can be inspired by all three approaches. Specifically, ABMs can enter into play to relax perfect rationality and homogeneity assumptions while still mimicking the micro-founded approach on which classical economic models rest. In Section 4.1, we propose an example of how such an approach can be put in place.

4 The complexity of interorganizational networks

The use of AMBs can be particularly suited to studying interorganizational network formation when considering the heterogeneity of agents and the complexity of their interactions.

The first source of complexity, which is inherent to every interorganizational network, is that organizations themselves are composite entities made up of several interacting individuals. As Hidalgo sharply puts it, "Organizations are networks embedded in other networks and their survival depends as much on their internal structure as on the position they hold in their networked environments," (Hidalgo 2011, 567). Both theoretical and empirical papers dealing with interorganizational networks usually consider one level of analysis of these nested interactions, i.e., the organization-organization level, and disregard composite interactions happening across divisions, teams, units, and individuals (Lumineau and Oliveira 2018; Ahuja, Soda, and Zaheer 2012). Interorganizational relationships and networks are inherently multi-level phenomena (Zaheer, Gözübüyük, and Milanov 2010); however, the focus on one single level of analysis has been common for most research on the topic. In this respect, such a limited focus can have major consequences on the managerial analysis of interorganizational relationships and networks: (i) it may lead to overestimating or underestimating the explanatory power of the theoretical mechanisms found at one level of analysis; (ii) it may minimize tensions that could arise across intraorganizational and interorganizational levels of interaction; and (iii) it may significantly reduce the meaning of network dynamics nested across these levels (Lumineau and Oliveira 2018, 445).

The second source of complexity is related to the different types of interaction that can develop between any two organizations. This kind of complexity can be connected to the famous argument of relational embeddedness by Granovetter (1985): when agents interact, their motivations, beliefs, and interactions will inevitably be characterized by both economic and social aspects. This intuition is the basis of so-called "new economic sociology", and has had a tremendous impact on the study of interorganizational networks. Social network scholars have used the instrument of multiplexity, i.e., "the co-existence of more than one type of relationship between two actors" (Ertug, Brennecke, and Tasselli 2023, 3) to represent and study this complexity. Think, for instance, of banks that may have relationships with other banks in the short-term money market, as well as actively trading derivatives over-the-counter with another (non-necessarily disjoint) subset of banks. Ertug, Brennecke, and Tasselli (2023) have recently provided an extensive review on the topic, clarifying how multiplexity produces three kinds of effects on network exchanges. Firstly, it is related to *relational harmony*, i.e., the valence in the overall relationship between two actors (Ertug, Brennecke, and Tasselli 2023; Lumineau and Oliveira 2018). For instance, the presence of both social interaction and economic exchange can increase the perceived value of the relationship for the two organizational actors (Ferriani, Fonti, and Corrado 2013). But scholars have highlighted how multiplexity can also reduce relational harmony, or produce mixed effects. Secondly, multiplexity can have an effect in terms of *task complementarity.* Task complementarity is increased when the presence of, for instance, formal and informal ties between two organizations increases the synergies in the exchange. However, it can also be reduced when the presence of multiplex ties constrains the agency of the single organization (Shipilov and Li 2012). Finally, multiplexity can also be related to the extension of the *relational scope* of interorganizational relationships, due to improved knowledge exchange, trust, and flexibility (Provan and Milward 2001).

As can be seen from this brief categorization, the presence of different types of ties (i.e., cooperation and competition; friendship and collaboration; formal and informal relationships; etc.) between two organizations can have complex effects on emerging relationships. As an example of how these sources of complexity result in elaborate and effective network structures, Ferrary and Granovetter (2009) make use of complex network theory (Newman 2003; Barabâsi et al. 2002) to explain the innovation performance of the Silicon Valley regional network: they characterize such network as complex because of the number and the heterogeneity of the actors involved, and because of the multiplex and decentralized nature of the relationships among them. This attention to the features of interorganizational networks that render them complex has been growing in recent years, and several scholars have used ABMs to complement other empirical and theoretical methods to grasp the essence of this complexity. For instance, Tatarynowicz, Sytch, and Gulati (2016) use an ABM to compare emerging structures of interorganizational networks (given different characteristics of the firms and of the industries in which they are embedded) to real-world structures. In this way, the authors are able to "advance an environmental contingency theory of network formation, which proposes a close association between the characteristics of actors' environment and the processes of network formation among actors" (Tatarynowicz, Sytch, and Gulati 2016, 53), by leveraging the power of ABMs to depict emerging systems, complex dynamics, and unconstrained micro-macro spanning mechanisms. Another influential paper that makes use of ABM is the one by Sytch and Tatarynowicz (2014), where the authors use an ABM to study how micro-level properties (i.e., the balance of positive and negative ties in dyads and triads) scale up to macro-level structural features of the network.

These examples show that ABMs are an extremely powerful lens to understanding dynamics in interorganizational networks. However, we also want to emphasize how the use of ABMs can further enrich our understanding of complex and especially multiplex network structures, focusing in particular on the formation of such structures. To sketch how this could possibly be done, we provide an exemplary model in the next section

4.1 An example of interorganizational network formation

In this section, we present an example of an agent-based model of network formation, broadly inspired by the version of the connection model described in Jackson (2005), emphasizing some novel features that appear to be especially relevant in an interorganizational setup. In particular, firms are heterogenous, in terms, say, of the contribution they can give to a partnership or to an organization. Links are also potentially diverse, as described below, and a multiplicity of bonds are possible so that the costs/benefits depend on the couple of agents involved in the tie. The heterogeneity of nodes and the multiplexity of the network are likely to be important in explaining how networks form and are ultimately arranged. Muliplexity not only refers to different types of ties among the same set of nodes (as explained above), but can also have a structural underpinning if we consider actors belonging to different *layers* of the network.

Assume N organizations create links that can be interpreted as formal commercial or productive bilateral agreements capable of adding value to the activities of the firms.

The cost of creating and maintaining a link is $c > 0$. Initially, the network is empty ($G_0 = \emptyset$), meaning that no agreement is yet in place. Agreements do not emerge in a vacuum and are based on another network G' of familiarity (or "friendship"). Formal agreements are less costly or, alternatively, require less effort and work better, if good informal contacts are (already) established between the two parties. We assume G' to be a complete network with two types of links, occurring with probability p and $1 - p$: good links are characterized by a positive discount $\epsilon > 0$ that will diminish the cost of entering into a formal agreement; neutral links have null discount. In an equivalent interpretation, G' can be thought of as an Erdős-Rényi graph $G(N, p)$ where links are randomly activated with probability p to denote the presence of a non-null discount ϵ.

Hence, signing an agreement with a "friendly organization" only costs $c - \epsilon$ and may be more advantageous, *ceteris paribus*, than forming a formal tie in G with a neutral neighbor in G', as the cost would remain c in this case. The presence of these two layers of the network is meant to be a simple example of multiplexity (formal and informal links have different roles and functions) but, clearly, another interpretation is that the cost of links in G are variable (as it may often be the case in the landscape of organizations).

The benefits of setting up a formal agreement in G depend on the organizations and, for simplicity, we assume that the contributions can be high or low, depending on the different routines or technical capabilities of the

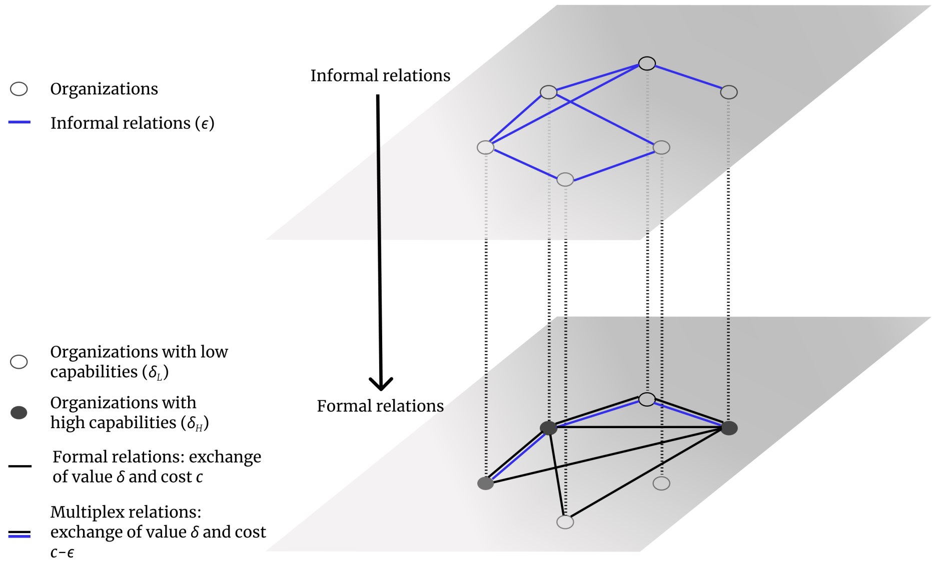

Figure 1: Visual representation of our example of a multiplex interorganizational network.

organizations. Hence, each node is labeled with positive $\delta \in \{\delta_H, \delta_L\}$, with $\delta_H > \delta_L$, signaling whether the organization can carry a high (or low) benefit in the case of an agreement; a visual representation of our modeling example is given in Figure 1. Observe that our setup clearly exemplifies that heterogeneity can be introduced using different modeling options and, in this case, profits depend mainly on the nodes, and costs are affected by the links (or, alternatively, by the multiplexity of the layered formal and informal ties).

We now describe the dynamics leading to the formation of the formal network of agreements G_t, where the time dependence makes clear that it is an incremental process (i.e., formal links can be added or deleted in every period), organizations do not have full knowledge of the environment, and G' is fixed at the inception.

At every period $t = 1, ..., T$, potential (actual) formal links are randomly drawn and can be added (deleted, replaced). More formally, let $V_i(G_t)$ be the benefit (or utility) of the i-th agent when the network of formal agreements is G_t. Purposive agents seek to increase their V_i, updating or modifying G_t if this is convenient according to the following three elementary operations:

1. Add a link: a random link $ir \notin G_t$ is drawn and added if

$$V_i(G_t + ir) \geq V_i(G_t) \text{ as well as } V_r(G_t + ir) \geq V_r(G_t);$$

2. Delete a link: a random link $is \in G_t$ is drawn and deleted if either

$$V_i(G_t - is) \geq V_i(G_t) \text{ or } V_s(G_t - is) \geq V_s(G_t)$$

3. Replace a link: the random links $ir \notin G_t$ and $js \in G_t$ are simultaneously added and deleted, respectively, to/from the network G_t if

$$V_i(G_t + ir - js) \geq V_i(G_t), V_r(G_t + ir - is) \geq V_r(G_t)$$

   and either

$$V_j(G_t + ir - js) \geq V_j(G_t) \text{ or } V_s(G_t + ir - js) \geq V_s(G_t).$$

In the previous description, we denoted by $G + ij$ the network G to which link ij is added and by $G - ij$ the network from which link ij is removed. Observe that adding a link requires consensus by both ends of the link: ir is added only when the utilities of nodes i and r mutually increase. In contrast, removing a link is a unilateral decision, reflecting the idea that it takes two to sign an agreement, but either party can rescind the deal at any time. While this stipulation looks reasonable in the modelization of formal pacts, it may obviously be inappropriate in other cases (for instance, a web page can always be enriched with a link to another page with no need to ask the target for permission).

A possible definition of $V_i(G_t)$ for the i-th agent, in line with Jackson and Wolinsky (1996), is

$$V_i(G_t) = \sum_{j \neq i} \left(\frac{\delta_i + \delta_j}{2} \right)^{g_t(i,j)} - \sum_{j \in N_i(t)} (c - \epsilon_{ij}),$$

where $g_t(i,j)$ is the length of the (shortest) path between nodes i and j and $N_i(t)$ is the set of the neighbors of i (at time t). The above utility has two intuitive components: the first sum (over all the links of the formal network) provides value based on the delta of nodes that can be reached through direct or indirect agreements; the second sum accounts for the costs of maintaining relationships with direct neighbors, and shows the multiplexity effect of the layer of "discounts" $\epsilon_{ij} \in G'$. Loosely speaking, we expect firms with high capabilities (δ_H) to be technical hubs and well-connected, nodes with many positive ϵ to lubricate relationships and help bridge different formal sub-networks.

Given a value function v, a network G^* is said to be efficient with respect to v if $v(G^*) \geq v(G)$ for any other network G. We assume in this discussion that $v(G) = \sum_{i=1}^{N} V_i(G)$.

Figure 2 shows a sample of the networks formed when running the previous algorithm for 600 periods, which are sufficient to reach a pairwise stable configuration in which no agent has the incentive to add or remove links.[2]

The networks are obtained when the number of nodes is $N = 16$, 8 of which contribute with $\delta_H = 0.8$ and the other 8 with $\delta_L = 0.3$; the cost of a formal link is $c = 0.7$; the "discount" due to friendship is $\epsilon = 0.3$; and $p = 0.15, 0.40, 0.75$ in the first, second, and third row of Figure 2, respectively. The technical capabilities of the firms are markedly heterogeneous; there are non-negligible costs of setting up a formal tie; and we explore different underlying structures of the static informal ties in G', which can be sparse for $p = 0.15$ and increasingly dense when $p = 0.40$ and 0.75.

Among the numerous insights that can be gained from our example, we emphasize only some of the most relevant differences with respect to Jackson and Wolinsky (1996), which in a sense is a special case in which $\delta_H = \delta_L$ and p or ϵ are null. Recall that, depending on the parameters, the efficient symmetric equilibrium was found in Jackson and Wolinsky (1996) to be either the empty network or a star or a complete graph.

The first row of Figure 2 shows that when the informal network is sparse, for $p = 0.15$, the resulting pairwise stable equilibrium network can have multiple disconnected components. For instance, in two cases, four organizations do not have any formal link with others, due to their low capacity $\delta = \delta_L$

2. A network G is pairwise stable if

$$\forall ij \in G, V_i(G) \geq V_i(G - ij) \text{ and } V_j(G) \geq V_j(G - ij)$$

and

$$\forall ij \notin G, V_i(G + ij) > V_i(G) \implies V_j(G + ij) < V_j(g).$$

The first condition ensures that no link deletion makes both agents strictly better off. The second condition states that if adding a link would increase the utility for i, no other agent j would accept the addition.

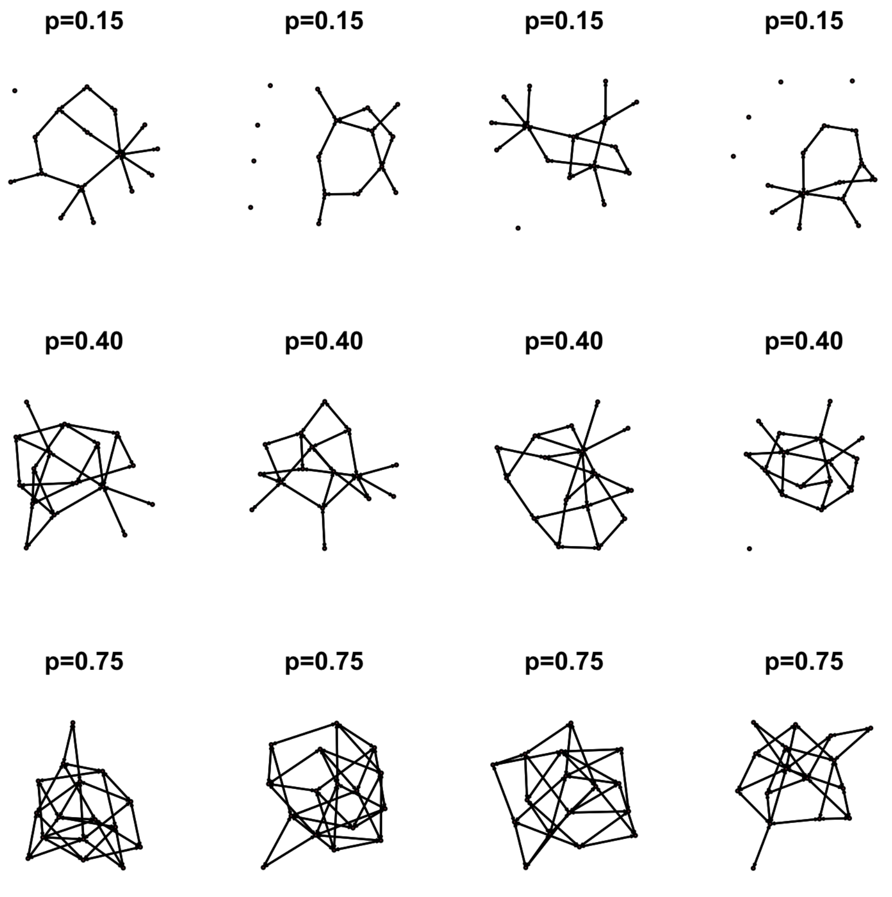

Figure 2: Pairwise stable networks formed using the add-delete-replace algorithm described in the text, for different values of $p = 0.15, 0.40, 0.75$ (the density of the informal network) in the first, second, and third row.

and the absence of informal links, which we may call a "lack of social capital". More importantly, the depicted networks show that a star is unlikely to appear: rather than seeing a unique central broker (providing efficient access to every node), we observe the emergence of a clearly visible multi-hub structure, where several organizations play the role of local hubs and bridge different "communities". This outcome is due to the heterogeneity of nodes (in terms of capacity) and to the multiplex nature of the links (availability of valuable friends).

However, there is also another fundamental reason for this outcome: if all agents are randomly offered the chance to create formal links, several of them will typically begin to form sub-networks with friends or partners contributing δ_H. Such seminal and initially disjoint structures will persist in the pairwise stable equilibrium that is reached. In other words, unless some orchestration is in place and one single agent is repeatedly given the privilege of being the first mover, becoming the tentative center of the star and offering other nodes strong incentives to join in, the equilibrium network will feature several hubs and will be affected by the path-dependence inherent in a dynamic formation process. As brightly pointed out by Axtell (2007), the risk of believing that *efficient* equilibria are the only interesting configurations is strong when reading neoclassical papers. The agent-based example reveals that simulating a (realistic) sequence of actions on the part of organizations is very likely to produce pairwise outcomes that differ, in many respects, from the efficient equilibrium singled out in theoretical models.

The second and third rows of Figure 2 show, as expected, that the number of formal agreements increases with the density of the underlying informal network. The second row depicts the case $p = 0.40$ and, still, there may be disconnected nodes, albeit with a lower probability. When p increases to 0.75, in the third row, we can visually detect how the formal network that is formed dynamically "approaches" the complete graph that is among the efficient outcomes in Jackson and Wolinsky (1996). Observe that an increase in p *de facto* reduces the average cost of formal links, being discounts increasingly at hand. In the limit case with $p = 1$, the cost becomes $c - \epsilon$ and, hence, we may conceptually enter the parametric regime generating a complete graph as in the connections model by Jackson and Wolinsky (1996).

Agent-based models are extremely well-equipped to investigate the dynamics of the process under scrutiny. The networks shown previously were the *final* outcome of such a process, but a closer look at the *dynamics* is represented in Figure 3. For $p = 1/3$ and $c = 0.4$, the green line shows the time evolution of the number of formal links between organizations that have no informal links (i.e., the number of links $ij \in G$ such that $\epsilon_{ij} = 0$ in G'). The blue line depicts the number of links that are supported by an informal friendship (i.e., the formal ij is supported by $\epsilon_{ij} = \epsilon > 0$).

The hump-shaped green curve (with one standard deviation above and below the mean) demonstrates that, in the initial phase when the formal network is close to void, formal links are quickly established even between non-friends, since the benefits of collaboration and the network effects are nevertheless generated for the nodes. As further formal links are explored and added to the network, after about 50 steps, agents start *replacing* some links they have established with others that provide the same high benefits in terms of δ but are negotiated with "friends" (who make the deal more convenient

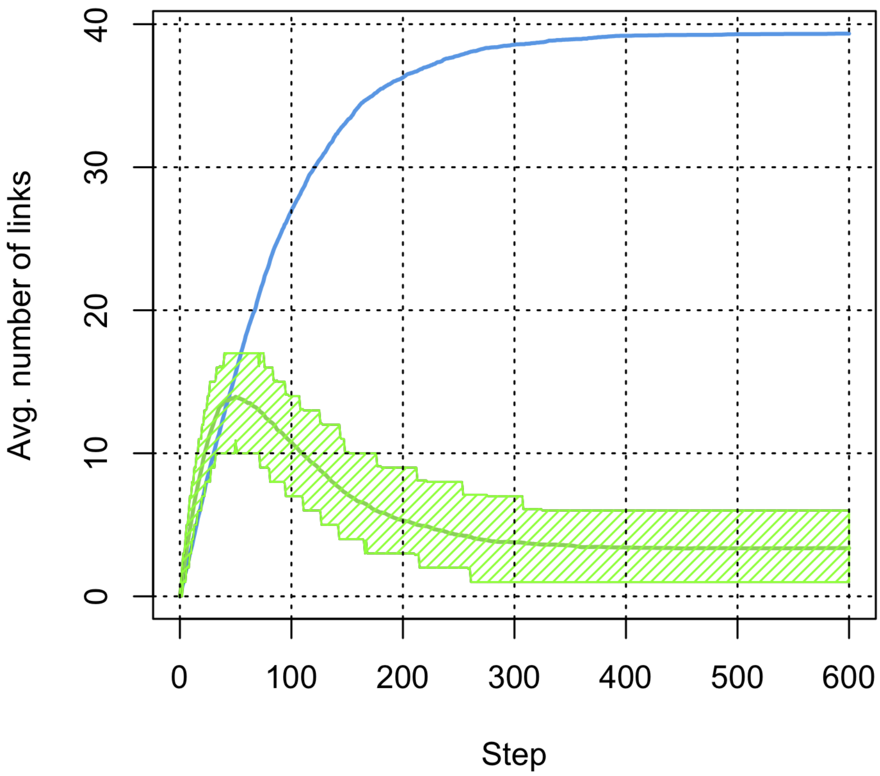

Figure 3: The blue line shows the average number of formal links with friendly organizations as a function of time, for $p = 1/3$ and cost $c = 0.4$. The green line shows the average number of formal connections established with unfamiliar organizations (one standard deviation above and below the mean is also shown based on 100 simulations).

because of $\epsilon_{ij} > 0$). In other words, neutral links (i.e., established with non-friends) are temporarily used at the beginning of network formation, and improve utilities of agents through direct (if $g_t(i,j) = 1$) and indirect effects (recall that, if $g_t(i,j) > 1$, utility flows through the average of the technical abilities raised to the distance). Intuitively, when there are enough formal links, it is convenient to maintain mostly direct links with friends, reducing costs, and still securing indirect benefits with members of the network at larger distances. After many steps, when an equilibrium is reached or closely approximated, the vast majority of formal links in this parametrization are between friends: hence, it could be argued that the underlying informal structure, besides the mere technical merit of the components, determines to some extent which formal network is established.

This rise and fall of links with neutral partners is an interesting feature of the model, and appears to dynamically capture the instrumental role of non-friends; agents quickly discover prospective partners, who then are abandoned, allowing links to be reconfigured by trial and error and partnerships to be rewired differently (and more conveniently) at a later stage.

5 Conclusions

The present chapter has outlined current approaches and possible extensions on the topic of interorganizational network formation. Interorganizational networks present some distinct features in terms of networking (i.e., the need for bilateral agreements, trust building, etc.) that have to be taken into account when studying the formation of such structures. We have covered closed-form models of network formation, highlighting their limits in terms of representing realistic formation processes of relationships among independent organizations. On the contrary, we underline how ABMs are capable of allowing a finer-grained and time-oriented perspective on such processes.

In particular, ABMs allow for relaxing the constraints imposed by a classical economic approach introducing heterogeneity, learning, bounded rationality, and behavioral rules. All such traits can be related to concepts such as characteristics, motives, and even strategic choices of the organizations. By looking at the different characteristics of individual firms – as we did in our example introducing heterogeneity in terms of organizations' capabilities – we can understand which network architectures emerge, even relaxing some restricting assumptions on the mechanisms of network formation. Moreover, ABMs enable us to observe the dynamics of network formation that develop over time, directing future empirical research toward critical factors in this underdeveloped area of research (cf. Ahuja, Soda, and Zaheer 2012; Harini and Thomas 2021).

As we have shown, the study of interorganizational networks, including their complexity, is becoming more and more relevant (Ferrary and Granovetter 2009; Shipilov et al. 2014). In particular, the study of the multiplexity of interorganizational relationships is burgeoning (Moretti, Piccione, and Tolotti 2023). Despite the advancements of extant research on the study of the implications of such multiplexity (Ertug, Brennecke, and Tasselli 2023), it is less well understood how multiplexity develops: "one neglected but promising area of research is how relations between people (such as friendship) turn into multiplex relations between organizational entities," (Shipilov et al. 2014, 455). At the same time, understanding how the multiplexity of ties influences the dynamics of interorganizational network formation and evolution could significantly enrich our knowledge about such kinds of collaborative arrangements. With our example, we showed how the availability of an abundance of informal ties increases the density and decreases the centralization of formal collaborative ties among organizations (see Figure 2). More interestingly, we observed how, and under which timings, organizations develop and substitute single ties with multiplex ones (see Figure 3). This kind of insight into multiplex network dynamics potentially enriches our understanding of phenomena such as overembeddedness (Uzzi 1997), when organizations lock themselves into rich and closely-knit structures, ending up in myopic behavior and redundant knowledge exchange.

Concludingly, in this contribution, we discussed the importance of network formation and evolution when addressing interorganizational studies. In this respect, we have shown how the use of ABMs (drawing their building rules on mechanical, optimization-based, or economic approaches to network formation) could also help us gain a more thorough understanding of interorganizational network performance (Kim, Funk, and Zaheer 2023), an object that is still not clearly defined, and how such performance is related to network dynamics and functioning (Ryan Charleton, Gnyawali, and Oliveira 2022). We hope to see more research in this domain in the future, leveraging the richness and flexibility of ABMs.

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