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New Organizations in Complex Networks: Survival and Success

Caner Asbaş[1], Zühal Şenyuva[2], Şule Tuzlukaya[3]

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Abstract

Purpose: The present study investigates the survival and success of new organizations in the light of complex network theory.

Methodology: The empirical data was collected using the survey method from the technology park companies are analyzed with social network analysis. Two main methods were used in this study: descriptive statistics and social network analysis.

Findings: The findings indicate that new nodes appearing because of splitting up of bigger nodes from present or other related networks have a higher degree of centrality. In practice, this means that companies founded by former members of large-scale companies from these networks are more successful due to the ease in providing the flow of resources and information through previous links. This suggests that the imprint effect can be observed in the appearance, lifecycle, and performance of new nodes in complex networks.

Originality: The literature lacks studies on new organizations' lifecycle in complex networks despite the existence of studies about new organizations in organizational networks. This study examines the appearance, success, and survival of new organizations in networks by complex network approaches such as dynamism, dissipative structures, and uncertainties.

Keywords: complex networks, dissipative structures, new organizations, self-organization, uncertainty.

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[1] Corresponding author, School of Business, Atılım University, 06830, Ankara, Turkey, email: canerasbas@gmail.com; https://orcid.org/0000-0002-2315-565X.

[2] Program of Business Administration, Başkent University, 06790, Ankara, Turkey, email: zuhala@baskent.edu.tr; https://orcid.org/0000-0002-7987-0863.

[3] School of Business, Atılım University, 06830, Ankara, Turkey, email: sule.tuzlukaya@atilim.edu.tr; https://orcid.org/0000-0001-8244-6396.

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Introduction

Social network theory investigates organizations in a network environment, as the term implies (Soda, Usai, and Zaheer, 2004; Pacheco, York, Dean, and Sarasvathy, 2010; Whelan, 2011; Greenacre, Freeman, and Donald, 2013; Ghosh and Rosenkopf, 2015; Liu, Sidhu, Beacom, and Valente, 2017). In organizational networks, actors can have mutual links that will benefit them with access to resources, information, stronger business performance, and success (Banova, Mishkovski, Trajanov, and Kocarev, 2010; Öberg, 2012; Golonka, 2013; Mierzejewska and Dziurski, 2021). Our focus related to the social network theory lies in the investigation of the existence and features of relations because they provide the required resources for these establishments and increase legitimacy (Gulati, Dialdin, and Wang, 2005). However, the concept of legitimacy only refers to relations among organizations, excluding associated dynamics and complexities. What filled this gap was the emergence of complexity theory and its integration in the social network theory.

This study analyzed new organizations in complex organizational networks and evaluated them in a dynamic research base. Thus, it also focused on the opportunity of contributing to the complex network conceptualization by conducting an empirical study. Through this study, we highlight one of the underexplored issues in the network theory (cf. Parkhe, Wasserman, and Ralston, 2006).

Castells (2000) categorizes modern society as a "network society," followed by Webster's (2006) "information society," and others who refer to the concept of "digital society" (Berntzen and Karamagioli, 2008; Stratton, Powell, and Cameron, 2017; Bykov, Balakhonskaya, Gladchenko, and Balakhonsky, 2018; Golova and Sukhovey, 2018). This was due to the increase in information flow, digitalization process, links among people all over the world, and the effect of globalization (Klenk, Binnig, and Schmidt, 2000; Tate, Furtmueller, and Wilderom, 2013).

According to Morçöl and Wachhaus (2009, p. 45), a network can be defined as a "relatively stable and complex pattern of relationship among multiple interdependent and self-organizing elements, which also constitutes a self-organizing system as a whole." This definition implies the establishment of an organizational system by emphasizing stability features. On the other hand, a complex system can be also defined as "a pattern of relationship among adaptive, self-organizing and interdependent elements – a pattern that exhibits emergent properties" (Morçöl and Wachhaus, 2009, p. 46). This definition emphasizes adaptivity, namely the dynamic nature of organizational relations and properties. These two definitions have common elements – which are multiple interdependent relations and self-organization – and complementary elements: approach to stability, understanding of change, and coping with uncertainty. These complementary relations provide us with a new approach to organizations that can be named complex network theory. In this sense, complex network theory reflects an interdisciplinary approach that integrates these two views and focuses on modeling complex activities within the organizational environment (McKelvey, 1999).

Organizations generally encounter emergent or holistic processes due to the membership of networks (Lissack, 1999). Holistic properties that cannot be investigated by examining the parts of the network separately are generated due to this dynamism (Morçöl and Wachhaus, 2009). On the other hand, emergence is defined as “an overall system behavior that comes out of the interaction of many participants” (qtd. after Casti in: Lissack, 1999, p. 111). Therefore, emergent features cannot be predicted or foreseen with the information of the nodes owned by networks in isolated states (Lissack, 1999).

In this direction, Morçöl (2015) advises researchers to investigate the total system, its components, and dynamic relations together so as to develop a better understanding of networks and organizations. Complex network theory considers networks as units of analysis and analyzes them with stochastic approaches. Stochastic approaches are interested in the total system, and so they achieve results with statistical methods.

Integration of definitions regarding networks and complex systems with stochastic and totalistic views enables complex network theory to explain dynamic relations between organizations in networks. Despite their strong conceptualization in terms of dynamism, such as self-organization and self-regulation, appearance, survival, and sustainability of new organizations in complex networks are not studied deeply (Lissack, 1999; McKelvey, 1999; Morçöl and Wachhaus, 2009; Boisot and McKelvey, 2010; Lord, Dinh, and Hoffman, 2015; Jarvenpaa and Majchrzak, 2016).

The rest of the article is organized as follows. First, we will present a short literature review of complex network theory and new organizations in complex networks, followed by the presentation of three research questions. In the next section, we explain our data collection process, methodology, data analysis, and findings. We conclude this article by discussing the findings in the last section.

Literature Review

Complex Network Theory

A complex network can be described as an environment in which chaotic situations are natural, changes and their results are unpredictable, and stochastic processes are dominant (Yulmetyev, Hänggi and Gafarov, 2000; He and Shi, 2009; Yu, Chen, and Cao, 2011; Rossello, Canals, Oliver, and Morro, 2014). Complexity theories are useful to understand and investigate the organizational actions that change rapidly, therefore causing unpredictability (Lord et al., 2015). Accordingly, such systems may also sustain complex, adaptive, and self-organizing relations.

The prevalence of complex network theory is well documented in the literature, both theoretically and empirically. Theory mainly focuses on developments of conceptual frameworks (Lissack, 1999; Morçöl and Wachhaus, 2009) and interdisciplinary studies (Boisot and McKelvey, 2010; Lord et al., 2015; Jarvenpaa and Majchrzak, 2016; McKelvey, 1999). Empirical studies focus on uncertainty, change, decision-making, and effectiveness of organizations in complex environments (Sommer, Loch and Dong, 2009; Baumann and Siggelkow, 2013; Zhou, 2013; Billinger, Stieglitz and Schumacher, 2014; Morçöl, 2015; Faulconbridge and Muzio, 2016).

The integration of complexity studies into organization studies provides new concepts and terms for researchers. As this study focuses on the appearance, survival, and success of new organizations in complex networks, the key terms we must explain are dynamism, nonlinearity, dissipative structures, uncertainty, decentralization, and self-organization. These terms are useful to explain the relations between former and newer organizations, but also change mechanisms in complex networks.

According to the dynamism principle, systems work at the edge of chaos, which can be defined as a gap between stability and disorder (Condorelli, 2016; Lissack, 1999). At the edge of chaos, a significant level of energy is stored, and it appears stochastically in microstates (McKelvey, 1999). As this energy can be tracked with the postmodernist approach, chaos is viewed as the possibilities and opportunities for creation (Barley, 2010). Nonlinearity is another characteristic feature of the complex network (Morçöl and Wachhaus, 2009). Together with dynamism, nonlinearity is the dominant property of complex networks that disentangles them from conventional and stable organizational networks. Nonlinearity is defined as the disproportionate relation between variables (Morçöl and Wachhaus, 2009; Condorelli, 2016). According to the nonlinearity concept, small changes can lead to higher differences in outcomes, while big shifts in inputs may cause only small differences in results (Chandra and Wilkinson, 2017). As the third characteristic feature, we should mention the existence of a dissipative structure (Morçöl and Wachhaus, 2009). Dynamism and nonlinearity generate dissipative structures. Such dissipative structures tend toward disorder, disintegration, and dissolution due to the predisposition to increase entropy which reduces the level of regularity of the network. Dissipative structures can survive by perpetually receiving energy from and transmitting it to the environment (Boisot and McKelvey, 2010; Zuo, Liu, and Li, 2019). That is, dissipative structures require sources of energy and information to maintain their network structure in order to decrease the system's entropy and increase the level of regularity. Otherwise, the network may fully disintegrate. The coexistence of the dissipative structures phenomenon with uncertainty and dynamism makes complex networks nearly chaotic structures.

Uncertainty in complex networks results from various reasons – as explained above – and is inevitable (Lissack, 1999). Unlike the positivistic view that regards reality as stable and populated by facts that can be analyzed rationally by separately investigating parts of the whole, the perspective of complex network theory on uncertainty is more compatible with the chaotic world presented by the postmodernist view that rejects objectivity (Faulconbridge and Muzio, 2015). Thus, scholars view uncertainty as a natural outcome of the existence of various entities, while even the existence of uncertainties is assumed as a source for future opportunities of unrealized potentials (Lord et al., 2015). In terms of decision-making processes, there also appears an opposition between the traditional approach and the complex network theory. The former considers uncertainty to be a challenging factor in terms of assumptions, whereas the latter views uncertainty as the process' main element (Billinger et al., 2014). From this perspective, we may argue that change and uncertainty mechanisms encountered by organizations are generally underestimated and presumed chaotic and continuous (Lissack, 1999).

In complex networks, there are various reasons for the uncertainties such as internal and external environmental richness or different actors' interactions. Thus, the multiplicity of dimensions constitutes the basis for nonlinearities (McKelvey, 1999). The factors of *heterogeneity of agents* and *multiplexity of ties* emphasized by Ferrary and Granovetter (2009) create nonlinear interactions among agents. In contrast to traditional management practices, according to the complex network theory, uncertainties in the organizational environment should be accepted and managed instead of decreased (Lissack, 1999). There is more than one way available for managing uncertainties. Among them, hierarchy and supervision are the methods used most frequently (Zhou, 2013), which is to prepare for unexpected changes. Field relocation is another method, which helps to develop a strategic response (Faulconbridge and Muzio, 2015). This

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strategy involves rescoping, rescaling, and restaffing processes, while the main objective is to position the organization in a more favorable field that may provide competitive advantages against potential uncertainty. What is further beneficial of the method for uncertainty management is accurate information flow (Hallen, 2008).

Uncertainties in complex networks can be also related to the decentralization phenomenon. If incomplete and limited knowledge about the systems exists – as relationships among political, social, and economic actors – decentralization disallows reaching universal rules that regulate the overall system (Morçöl, 2015). Besides generating unpredictability and uncertainty, this view results in self-regulation and self-organization concepts.

Self-organization is a mechanism in the complex network theory that is used to explain the system's operations at the edge of chaos, which reaches higher-order complexity after chaos and decentralization emerge (Morçöl, 2015). This concept explains how the system works properly (Jarvenpaa and Majchrzak, 2016). Self-organization is an inherent property of organizations that allows them to identify networks' convergence (Morçöl, 2015). Complex network theorists state that the network means not pure market or pure hierarchical form (Morçöl and Wachhaus, 2009). The difference between hierarchy and network is the ability to operate with decentralization, which means networks are self-regulating and self-organizing. On the other hand, the self-organizing mechanism is enabled by the existence of information-processing capacities of the network's members (Morçöl, 2015). With this property, the mechanism shows distinctive features compared to the pure market type in which none of the participants has individual power to change the system.

Empirical studies on self-regulation and self-organization indicate that they can flush potential intrinsic and confidential power in the network and its members (Farh, Bartol, Shapiro and Shin, 2010). Flushing the potential may occur with the change in organizations' structures, response to the environment, transformation in relations with other actors, or establishment of new links with members or non-members (Morçöl, 2015). All these processes show two-sided and interdependent effects on the network and its nodes. As these processes have holistic and adaptive characteristics, they pave the way for higher complexity. They may also provide new organizations with more central positions in the complex network. On the other hand, they can threaten the current position of all organizations and endanger their survival and success.

New Organizations in Complex Networks

Despite the matter of how and under what conditions new organizations emerge being a subject of interest to organizational theories (Shane and Khurana, 2001), there is no consensus regarding the mechanisms of new organizations' formation (Dobrev and Barnett, 2005). The literature considers various factors' influence on new organizations' formation. Some examine the phenomenon at the society level, in line with Freeman's (1982) view that organizations emerge as a result of coordinated efforts of individuals rather than the actors' utilization of available opportunities. The relationship between the formation of new organizations and societal factors such as urbanization and the economy are investigated in this context (Stinchcombe, 1965). Another approach to the phenomenon is Hannan's and Freeman's (1989) ecological view, which links new organizations' formation to a combination of ecological factors and existing organizations in the population. This category comprises works that investigate the role of population dynamics (Hannan and Freeman, 1984) and technological change (Nelson and Winter, 1982) in new organizations' formation. Despite such studies, the appearance of new nodes and actors in complex networks is not thoroughly analyzed and investigated in the literature. Some researchers investigate new organizations' formation in organizational networks, but these studies are static and ignore the complex and dynamic nature of organizational networks, along with the relationships between nodes within complex networks. This situation results in the lack of strong analysis and deeper explanation of cases. Thus, complex network studies do not investigate new organizations' formation despite the strength of its analytic tools such as self-organization and self-regulation, which could explain the changes in relations between present and new nodes or the establishment of new nodes. When considered from this point of view, this study sought to bring studies on new organizations in networks to a dynamic research base, to contribute to and develop concepts in complex networks conceptualization such as dynamism, self-regulation, and self-organization.

If nodes are transferred from other networks or nodes appear out of nowhere, nodes in a network can appear divided into other large, medium-sized, and small nodes from the present or other related or unrelated networks, according to the theoretical foundation of network theory. This diversification corresponds to organizations established by former employees of medium and small-sized companies in related fields, as well as all former employees in unrelated sectors of any scale. For all these possibilities, to start an organization, we need the potential entrepreneur with access to resources who is willing to take risks (Shane and Khurana, 2001). This entrepreneur should identify the initial and long-term position of the organization, analyze its competitive advantages and environment, and forecast the potential opportunities and threats the

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organization may face (Riahi and Moharrampour, 2016). On the other hand, these tasks are extremely difficult in complex networks with nearly chaotic structures that show high levels of dynamism and uncertainty. The first research question investigates this situation:

> **RQ1:** How new organizations can appear in a complex network despite the existence of nearly chaotic structures?

Complex network theory explains that after the appearance of a new node, the complex network gains a new form due to the self-organization mechanism. These nodes of new organizations will establish relations with other nodes, influence and change relationships, and position themselves in a specific location in the complex network. Therefore, survival and sustainability can be achieved by new organizations. Besides the imprint effect, organizations' positions and performance are determined by the social and human capital (Hallen, 2008; Kase and Zupan, 2009). Belliveau, O'Reilly, and Wade (1996) mention that the actors with the potential to create relationships and mechanisms among organizations may be owners or managers. In this sense, company owners can be considered crucial in terms of establishing and maintaining network connections with other organizations (Collewaert, Vanacker, Anseel and Bourgois, 2021). Hallen (2008) states that connections as owners' social and human capital effectively sustain their businesses. From that viewpoint, entrepreneurs' personal connections are considered critical (Hallen, 2008). Moreover, potential partners can use any previous knowledge about the entrepreneurs' skills and abilities.

Although the initial position of new organizations is determined by the above features – because complex networks live "at the edge of chaos" – relations between nodes are not guaranteed for a long period. As a result, dissipative structures led by nonlinearity and dynamism in the complex network and tendency to increase in entropy drag organizations into dissolving and eliminating. Moreover, uncertainty and unpredictability in the complex network led by nonlinearities and dynamism again paint an unclear picture for organizations' decision-making processes. In this sense, new organizations and entrepreneurs suffer from high uncertainties of operations (Engel, Kaandorp, and Elfring, 2017). In such conditions, some organizations can achieve success while others are eliminated.

Since new organizations lack the necessary social and socioeconomic ties to reach key actors and established organizational structures, the liability of newness may easily lead to their elimination (Shane and Khurana, 2001). When the characteristics of complex networks are considered, we may claim that the liability of newness will impose a greater burden on organizations that are members of complex networks. Some methods – such as joint ventures, strategic alliances, and franchising – are proposed as solutions able to overcome the liability of newness and achieve success (Achrol, 1991; Bucklin and Sengupta, 1993; Doz, 1988). Other generic strategies, particularly for dynamic environments – such as the variety strategy, opportunistic strategy, and generalist strategy – can also be found in the literature (Cravens, Piercy and Shipp, 1996), but these are marketing-oriented and require an organizational perspective. Furthermore, firm financing and founding experience – along with social status – are related to the establishment and success of new organizations (Shane and Khurana, 2001). However, such an approach lacks the network relationships approach that is crucial for complex networks. In terms of the dichotomy between elimination and survival, in complex networks nodes that have some relations with other nodes before their appearance in the network will have an advantage, and this situation will increase their chances of survival. On the other hand, the nodes that have no or limited relations will try to establish these relations. Thus, the survival and sustainability of new organizations can also be achieved in this way. Accordingly, we pose the following research questions:

RQ2a: How can new organizations survive in complex networks despite new organizations' unsettled structures?

RQ2b: How do new organizations handle uncertainties in complex networks?

RQ3: How do new organizations become successful in complex networks?

Methodology

Study Context

Technology parks are places where technology companies are located to benefit from official tax incentives and reductions, network relations for technical and nontechnical issues, and networking benefits. These places have complex network properties for a reason. First of all, companies in technology parks are generally founded by young entrepreneurs who are mostly distant from establishing well-defined company structures. Second, due to bankruptcies and unsuccessful project management methods, the rate of new company closure is very high. On the other hand, newly established firms fill the gap that appears because of closures, and so there happens continuous and unstable circulation of technology parks' members. New organizations establish new relations with older members of a park's network and members of other networks,

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while the technology park gains a different characteristic. These features can be explained by their dynamism, nonlinearity, uncertainty, self-regulation, and self-organization. Another reason for uncertainties in technology parks is the subject on which each company works. The focus of companies in technology parks is high technology products such as software, radio frequency (RF) components, or robotic systems. These areas are not stable and settled; new trends may appear suddenly and deeply change entire areas. As a result, this situation makes the technological and financial future of the companies unclear. Ferrary and Granovetter (2009) argue that the complex nature of industrial cluster-like networks provides the clusters with the ability to recreate themselves to maintain and reproduce their innovative capacity. The non--homogeneity of actors and the multiple complex connections between these actors can support new organizations' formation (Ferrary and Granovetter, 2009). Although creating a new organization and sustaining its operations in a complex, chaotic, and high-pressure environment is a process with many ups and downs (Foo, Uy and Baron, 2009), newly established companies in technology parks find ways to cope with crises or problems caused by these fluctuations thanks to the self-regulated structures of complex networks that can rearrange themselves (Ferrary and Granovetter, 2009). Moreover, technology parks are commonly open systems that require resources to flow through the network from other networks such as governmental organizations or bigger networks, including large-scale companies to maintain the operation of the network (Basile, 2011). Otherwise, it may be fully disintegrated due to scarcity of resources. This situation can be explained with the dissipative structure conceptualization in complex network theory. In these aspects, technology parks are suitable for complex network studies.

Data Collection

As the data collection tool, we adopted the survey method. To satisfy participant anonymity and participant information security, the survey questionnaire was prepared with an online tool and was sent to eight chosen companies considered suitable for research questions in a selected technology park. To cover the content of the research questions, the questionnaire was prepared in three main categories: company founder's background, organizational and trade relations with other organizations, and factors to measure company success like growth rate or staff number.

Methodology

Two main methods were used in this study: descriptive statistics and social network analysis. With descriptive statistics methods, a deeper and more detailed picture of the complex network was achieved. Moreover, descriptive statistics provided statistical information about relations, backgrounds, and the success of respondent companies. The second method was social network analysis, which is a graph-theory-based mathematical model useful for analyzing network relations and visualizing connections between network nodes (members; Scott, 2010). Organizational networks and relations were the implementation areas for social network analysis (Tichy, Tushman, and Fombrun, 1979). With this method, network relations of the responding companies could be analyzed, visualized, and prepared in a form suitable for an interpretation related to the research questions.

Data Analysis

For social network analysis, we used the UCINET software (Borgatti, Everett and Freeman, 2002). In social network analysis, the applied measures were the degree of centrality, betweenness centrality, closeness parameters, Honest broker index, and brokerage scores. The degree of centrality is the number of connections of a node. It is calculated for each node separately. The lower degree of centrality means the node happens around the complex network's boundaries while the higher degree of centrality means the node is close to the center of the complex network system. Betweenness centrality indicates the brokerage level in the complex network. Brokerage score is the number of ordered pairs that have the appropriate group memberships brokered by a given vertex. The closeness parameter is another parameter that shows the place of the nodes in a complex network. Honest broker index in a network indicates incoming and reciprocated ties of trust-like relations. All these parameters depicted the statistical and mathematical image of the complex network, which was beneficial to achieve the results about network structure.

Results

Our survey provided us with answers from eight chosen companies. One of the companies was eliminated due to incompatibility with the study context. The tables present statistical outcomes.

Table 1 provides the activity areas of the respondent companies. In terms of main area activities, database and automation applications with artificial intelligence had the highest result of 28.57%. What these two with 14.29% were radio frequency and microwave electronics with robotics and electromechanics followed. Moreover, almost half of the respondent companies were interested in mobile applications and more

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than a quarter of them were focused on signal processing applications. These rates indicated that respondent companies were working on trendy technological topics, were notably open to further developments and new approaches – including unclear views about their future directions – and were even ready for changes in their main paradigms in a short period. Since these features had the characteristic of complex networks – which are nonlinearity, dynamism, uncertainty, and chaotic structure – the respondent companies could be used as a sample for complex network research.

Table 1. Results of activity areas of the respondent companies

Activity areas	Main area activity (%)	Side area activity (%)
Desktop software / Task software	0%	28.57%
Mobile applications	0%	42.86%
Database and automation applications	28.57%	0%
RF & Microwave electronics	14.29%	14.29%
Signal processing applications	0%	28.57%
Robotics / Electromechanics	14.29%	14.29%
Artificial intelligence	28.57%	0%
Data mining / Big data applications	0%	14.29%
Agricultural technologies	0%	14.29%
Other	14.29%	14.29%

Source: own elaboration.

Table 2. Demographic features of cofounders of the respondent companies

Number of Cofounders	Rate	Backgrounds of cofounders	Rate
1	42.86%	Former membership of a large-scale company in a related area	42.86%
2	28.57%	Former membership of a technology park company	0%
3	28.57%	Pure entrepreneurship	21.43%
+3	0%	Other	35.71%

Source: own elaboration.

Table 2 provides the number and background of cofounders among respondent companies. The cofounders of the respondent companies were in 42.86% former staff of large-scale companies in related areas, while 21.43% of them were purely entrepreneurs. The rest were former members of the medium-sized or small companies in related or unrelated areas. These rates indicated that new organizations in complex networks appear as reproductions or splits from bigger nodes from related or current network(s), transferring nodes from other networks or coming from nowhere via pure entrepreneurship.

Table 3. Bachelor's degree of cofounders of the respondent companies

Bachelor's degree	Rate
Electrical Engineering / Electronics Engineering / Electrical and Electronics Engineering / Electronics and Telecommunication Engineering	61.54%
Computer Engineering / Computer Science / Software Engineering	7.69%
Mechanical Engineering / Mechatronics Engineering / Aerospace Engineering	7.69%
Other	23.08%

Source: own elaboration.

Table 3 shows the fields in which the cofounders have bachelor's degrees. Note that electrical or electronics engineering and their versions dominated this section.

Table 4. Results of the companies for which the responding companies serve as subcontractors/product or service suppliers/developers/designers

Semi-governmental defense companies	Rate	Governmental organizations that relate technological areas	Rate
D#1	57.14%	G#1	0%
D#2	14.29%	G#2	0%
D#3	14.29%	G#3	0%
D#4	0%	G#4	28.57%
Other	0%	Other	14.29%
None	42.86%	None	57.14%

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Telecommunication companies	Rate	Software companies	Rate
T#1	14.29%	S#1	0%
T#2	14.29%	S#2	0%
T#3	0%	S#3	0%
T#4	14.29%	S#4	0%
Other	0%	Other	0%
None	57.14%	None	100%

Personal end users	Rate	Uncategorized customers	Rate
Yes	28.57%	Yes	71.43%
No	71.43%	No	28.57%

Technology park companies	Rate
P#1	14.29%
P#2	14.29%
P#3	28.57%
P#4	0%
P#5	0%
P#6	0%
P#7	14.29%
P#8	0%
Other	14.29%
None	42.86%

Source: own elaboration.

Table 4 reveals the business relations of the respondent companies. Approximately half of the respondent companies had business relations with semi-governmental defense companies, governmental organizations linked to technological areas, telecommunication companies, and companies from technology parks. On the other hand, very few had business relations with personal users, and none of them worked for software companies.

Table 5. Results of performance measures of the respondent companies

Duration of operations	Rate
Less than 1 year	14.29%
1–3 years	57.14%
3–5 years	0%
5–7 years	14.29%
More than 7 years	14.29%

Number of staff	Rate
1	28.57%
2	0%
3–5	42.86%
5–7	14.29%
+7	14.29%

Last financial growth rate	Rate
Negative	14.29%
Between 0% and 5%	14.29%
Between 5% and 10%	0%
Between 10% and 25%	28.57%
Between 25% and 50%	0%
More than 50%	42.86%

Last financial turnover	Rate
Less than 100,000TL	28.57%
Between 100,000TL and 250,000TL	0%
Between 250,000TL and 500,000TL	14.29%
Between 500,000TL and 1,000,000TL	28.57%
Between 1,000,000TL and 5,000,000TL	28.57%
More than 5,000,000TL	0%

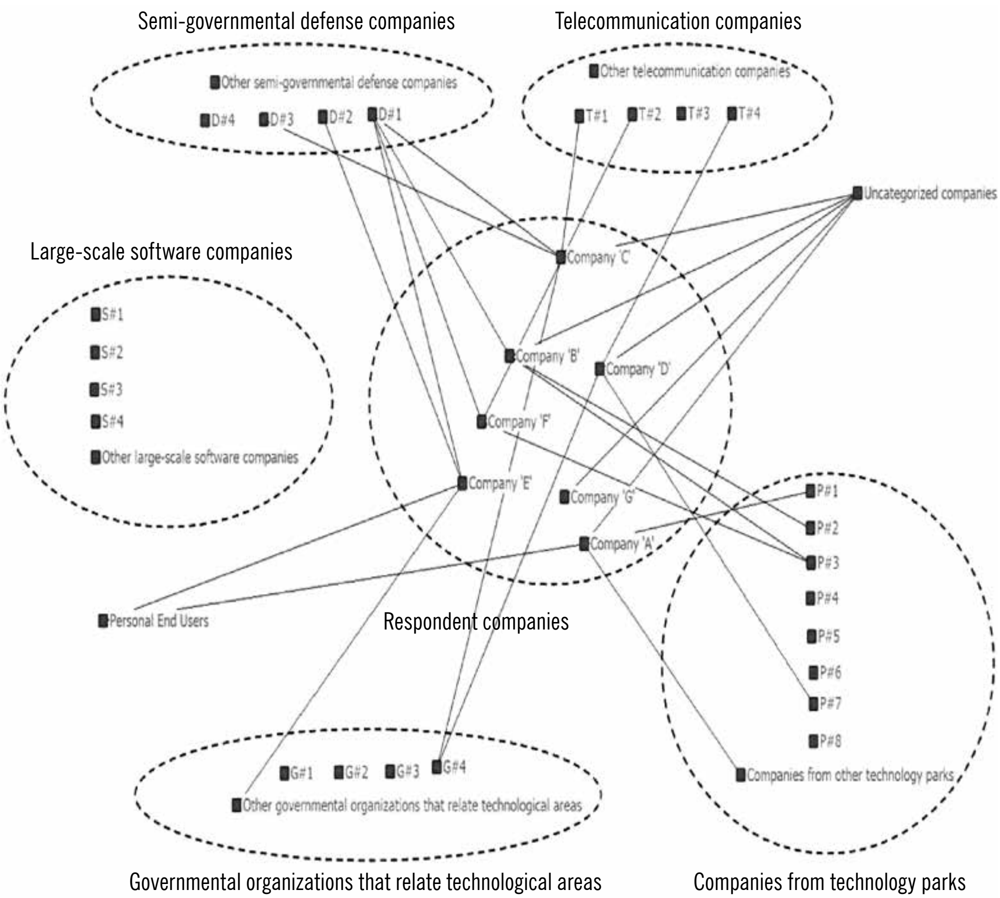
Source: own elaboration.

Table 5 provides the performance results of the respondent companies. More than half of the companies were operating for 1–3 years. Moreover, the last financial growth rate was higher than 50% for approximately more than half of the respondent companies. In terms of staff number and last financial turnover, we observed a more homogenous distribution among the specified categories.

Stage 1: Social Network Analysis with Unweighted Magnitudes of Relations

At this stage, social network analysis of respondent companies was performed by taking all the relations with equal magnitude. Figure 1 shows the social network map of the relations, while Tables 6–10 depict the network parameters calculated under this assumption.

Figure 1. Social network map with unweighted relations



Source: own elaboration.

Table 6. Degree of centrality parameters of the respondent companies with unweighted relations

Respondent companies	Degree of centrality	Normalized degree of centrality
Company A	4	0.108
Company B	4	0.108
Company C	5	0.135
Company D	4	0.108
Company E	4	0.108
Company F	3	0.081
Company G	1	0.027

Source: own elaboration.

Table 7. Betweenness centrality parameters of the respondent companies with unweighted relations

Respondent companies	Betweenness centrality	Normalized betweenness centrality
Company A	51.750	7.770
Company B	49.333	7.407
Company C	66.583	9.997
Company D	42.750	6.419
Company E	48.000	7.207
Company F	23.583	3.541
Company G	0	0

Source: own elaboration.

Table 8. Normalized closeness parameters of the respondent companies with unweighted relations

Respondent companies	Normalized closeness
Company A	5.598
Company B	5.632
Company C	5.649
Company D	5.547

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Company E	5.564
Company F	5.498
Company G	5.498

Source: own elaboration.

Table 9. Honest broker indices of the respondent companies with unweighted relations

Respondent companies	Size	Pairs	HBI0	HBI1	HBI2	nHBI0	nHBI1	nHBI2
Company A	4	6	6	0	0	1	0	0
Company B	4	6	6	0	0	1	0	0
Company C	5	10	10	0	0	1	0	0
Company D	4	6	6	0	0	1	0	0
Company E	4	6	6	0	0	1	0	0
Company F	3	3	3	0	0	1	0	0
Company G	1	0	–	–	–	–	–	–

Source: own elaboration.

Table 10. Brokerage scores of the respondent companies with unweighted relations

Respondent companies	CR	GK	RP	CN	LS	Total
Company A	0	0	0	12	0	12
Company B	0	0	0	10	0	10
Company C	0	0	0	18	0	18
Company D	0	0	0	11	0	11
Company E	0	0	0	12	0	12
Company F	0	0	0	5	0	5
Company G	0	0	0	0	0	0

Note: CR: Coordinator; GK: Gatekeeper; RP: Representative; CN: Consultant; LS: Liaison.
Source: own elaboration.

This analysis provided insight into the structure of the network constructed by the respondent companies and their related companies from other networks. On the other hand, the calculated network parameters did not generate meaningful information to answer the research questions. This situation happened because the magnitudes of each relationship between the nodes were taken into account as equal. However, this assumption concealed the strength, degree, and magnitude of relationships between the nodes and caused inconsequence. To overcome this issue, the magnitude of respondents' relationships was normalized by multiplying proper weights

Stage 2: Social Network Analysis with Weighted Magnitudes of Relations

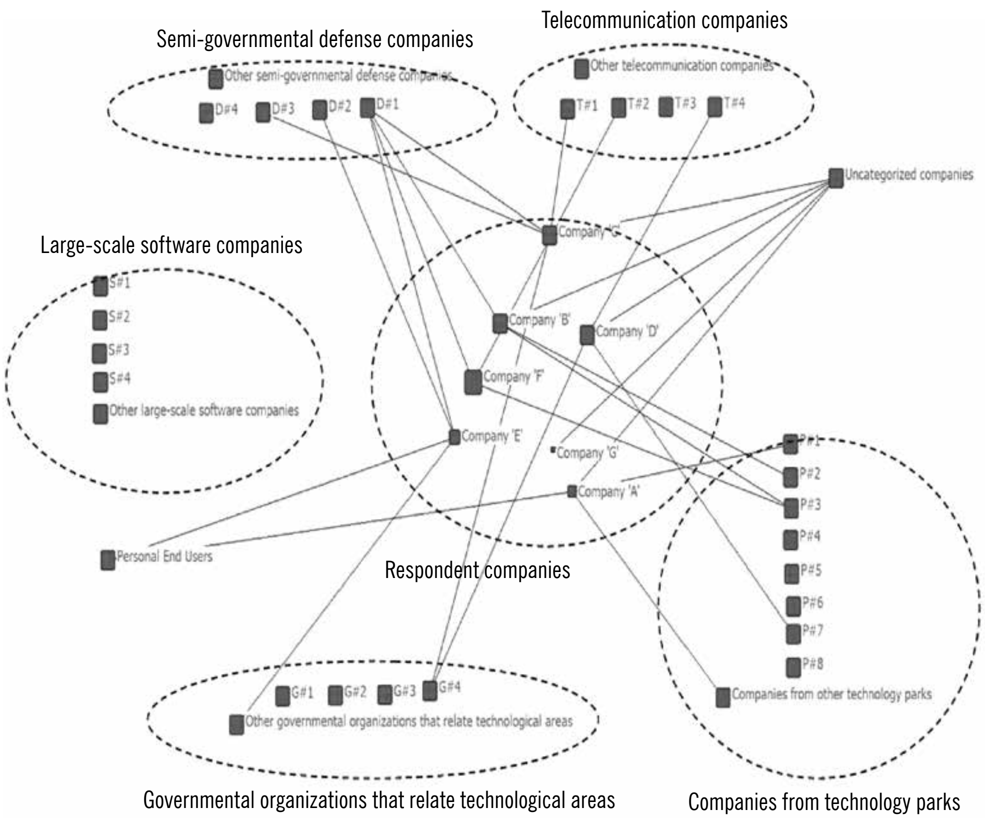
The strength of the relationships between the nodes could be related to the resources flow levels. As the respondent companies were subcontractors/product or service suppliers/designers/developers for the nodes from other networks, the resources flow levels could be measured via the amount of money emitted by the node of respondent companies, namely their financial turnover rate. The financial growth rate was another characteristic that allowed us to measure the strength of the relationships because it was directly related to the financial turnover rate in the preceding year. Another measure for the strength of relations may be the number of years the company operated because scholarship expects the relations will become more established, stable, and strong over time. Moreover, nodes' sizes were indicators of their position and effect in the complex network. We used staff number to measure the size of the nodes.

The four specified parameters – financial turnover, financial growth rate, staff number, and operation years – were normalized and combined as an indicator of the nodes' survival and success. We expected to observe an increase in financial turnover and financial growth rate with an increase in staff number and operation years. Therefore, financial turnover and financial growth rate were normalized with respect to both staff number and operation years. After all, it is normal for a company with a high success rate to increase its staff number over time. This means staff number should be normalized by operation years. In this way, we proposed to weigh the relationships of the nodes with the following equation:

$$C = T/S + T/Y + G/S + G/Y + S/Y + Y$$

in which T is the score for financial turnover, G is the score for financial growth, S is the staff number, and Y is the operation year. The network parameters calculated by considering the weights assigned according to the proposed equations are depicted in Tables 11–15.

Figure 2. Social network map with weighted relations



Source: own elaboration.

Table 11. Degree of centrality parameters of the respondent companies with weighted relations

Respondent companies	Degree of centrality	Normalized degree of centrality
Company A	22.000	0.030
Company B	44.000	0.059
Company C	44.250	0.060
Company D	47.333	0.064
Company E	34.000	0.046
Company F	60.000	0.081
Company G	4.333	0.006

Source: own elaboration.

Table 12. Betweenness centrality parameters of the respondent companies with weighted relations

Respondent companies	Betweenness centrality	Normalized betweenness centrality
Company A	51.750	7.770
Company B	49.333	7.407
Company C	66.583	9.997
Company D	42.750	6.419
Company E	48.000	7.207
Company F	23.583	3.541
Company G	0	0

Source: own elaboration.

Table 13. Normalized closeness parameters of the respondent companies with weighted relations

Respondent companies	Normalized closeness
Company A	5.598
Company B	5.632
Company C	5.649
Company D	5.547
Company E	5.564
Company F	5.498
Company G	5.498

Source: own elaboration.

Table 14. Honest broker indices of the respondent companies with weighted relations

Respondent companies	Size	Pairs	HBI0	HBI1	HBI2	nHBI0	nHBI1	nHBI2
Company A	4	6	6	0	0	1	0	0
Company B	4	6	6	0	0	1	0	0
Company C	5	10	10	0	0	1	0	0
Company D	4	6	6	0	0	1	0	0

Company E	4	6	6	0	0	1	0	0
Company F	3	3	3	0	0	1	0	0
Company G	1	0	-	-	-	-	-	-

Source: own elaboration.

Table 15. Brokerage scores of the respondent companies with weighted relations

Respondent companies	CR	GK	RP	CN	LS	Total
Company A	0	0	0	12	0	12
Company B	0	0	0	12	0	12
Company C	0	0	0	20	0	20
Company D	0	0	0	12	0	12
Company E	0	0	0	12	0	12
Company F	0	0	0	6	0	6
Company G	0	0	0	0	0	0

Note: CR: Coordinator; GK: Gatekeeper; RP: Representative; CN: Consultant; LS: Liaison.
Source: own elaboration.

The social network analysis diagram showed that the company with the highest degree of centrality was company F, while companies B, C, and D share the second position with close centrality values. Company G had the least centrality. These results are compatible with the fact that company F had the highest financial growth rate and financial turnover, although it had the lowest operation years number and staff number. Moreover, companies B, C, and D had the second-highest financial growth rate and financial turnover rates with the mid number of staff and operation years. Besides, company G has the lowest centrality due to the lowest financial growth rate and financial turnover. On the other hand, in terms of betweenness centrality, company C showed the best and company G the worst result. These results agreed with the performance criteria that indicated company C has the largest staff number and one of the highest turnovers. In terms of normalized closeness, the respondent companies had very close scores, with a slight advantage of company C. Closeness parameter included information for both direct and indirect causes, but we did not use this parameter as an indicator since the scores were very close for each respondent company. In terms of brokerage scores, only the score "Consultant" was nonzero for all respondent companies except company G. The company with the highest "Consultant" score was company C, while companies A, B, D, and E had the same score in the second position. The company with the worst score was company G. The score "Consultant" indicated that the current node connected two unconnected actors from similar categories. These results showed that company C had a lower relative differentiation in its business relation, while company F – the one with a lower nonzero score "Consultant" than company C – had diversified its portfolio relatively more than company C.

While we examined these companies in terms of cofounders' backgrounds, we saw that all the companies with the highest degree of centrality and best performance results were founded by former members of large-scale companies in related areas. Besides, companies A, E, and G with no founders with experience at large-scale companies had the lowest degree of centrality and the lowest financial turnover rates. This situation revealed that the respondent companies founded by former members of large-scale companies were more successful than the ones founded by others such as pure entrepreneurs or former members of medium-sized and small organizations. Compared to the results of weighted and unweighted network relations, the change occurred only in a degree of centrality. The degree of centrality is a significant indicator of company success because higher centrality can be inferred as a stronger position in the network. When we put respondent companies in the order of degree of centrality, we could see that the first four companies with higher centrality have at least one or more cofounders who are former members of large-scale companies in a related area.

Empirical results indicate that new nodes that appear from divisions of previous bigger nodes from present or other related networks can rapidly establish strong and dense relations with the nodes they break up. Moreover, such new nodes become able to transfer, clone, and benefit from already established relations among the nodes they divide. Such a hybrid structure emerges from the combination of existing ties with the previous ones. Consequently, the choices related to past relationships will have an imprinting effect on future ones. These results are compatible with the network memory approach of Soda et al. (2004), in which the performance of nodes in a social network is significantly affected by previous ties and structural holes.

Furthermore, the new nodes due to the division of bigger nodes from present or related networks can establish stronger relations with the bigger nodes. Thus, the new nodes can reach more resources and information with respect to other new nodes that appear due to the division of any nodes from irrelevant networks, medium-sized or small nodes from present or related networks, or that come from nowhere. In this manner, the new nodes can have a surplus of resources, which strengthens the new nodes and lets them survive despite their unsettled structures. Moreover, due to the stable and steady flow of information from the bigger nodes, these new nodes gain security against uncertainties and procure easier access to resources and safety against uncertainties.

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Thus, the new nodes can become more successful in complex networks despite the dynamic and chaotic structures of such networks.

Discussion and Conclusions

The complex network theory provides previous network approaches to organizations with a dynamic view by integrating the elements and perspectives of complexity theory. Moreover, the complex network approach leads to useful and beneficial expansions of static views with its concepts and vocabulary such as “self-regulation” and “dynamism”. Although the complex network theory can better explain the appearance of new nodes and their lifecycles while being suitable for empirical studies, this area remained a considerable gap in research. Our study was conducted to fill this gap and contribute to the literature by both explaining the appearance/emergence and lifecycle stages of new nodes and implementing empirical studies in complex networks.

Our study results showed that the companies founded by former members of large-scale companies in related areas are more successful than the companies founded by former members of medium-sized and small companies in related areas, former members of companies from irrelevant areas, and pure entrepreneurs. The companies founded by former members of large-scale organizations in related areas can gain benefits from their founders’ previous relations in the field. Theoretically, this situation indicates that the new nodes appearing from divisions of bigger nodes can easily integrate the present and related networks, provide condense and useful flow of resources and information, and in this way, resist problems caused by the chaotic structure of complex networks, thus withstanding uncertainties. On the other hand, the nodes appearing in other ways encounter more difficulties to growth, hang by a thread led by the nature of complex networks, and are more prone to dissolution.

Prior research shows that the professional experience of firm founders is very effective in the survival and success of new organizations (Duchesneau and Gartner, 1990; Haveman and Cohen, 1994). In the context of social capital, founders of new organizations with more experience will positively impact the organization’s success due to their ability to form new ties (Bamford, Bruton and Hinson, 2006). For the survival of new organizations, this ability is equally as vital (Neergaard and Madsen, 2004). As a result, the founder’s role extends beyond leadership to include the formation of organizational ties, as social capital is an important source of competitive advantage (Bamford et al., 2006). This advantage significantly impacts the survival and success of new organizations (Spender, 1996; Nahapiet and Ghoshal, 1998). This study demonstrated that this task also applies to new organizations in complex networks. Our findings showed that establishing relationships with large-scale companies in related fields is highly important for organizations in complex networks for their survival and success.

Although there are studies that indicate the significance of social capital, human capital, and network relations for the survival and success of new organizations, the literature lacks the works that would explain the required type of these capabilities. This study shows the importance of founders' professional carrier in large-scale companies in related fields, along with network relationships with such companies, for the survival and success of new companies. This situation implies that scholars should investigate not only the effect of social and human capital or network relations but also their mechanisms, types, and nature so as to achieve more accurate and detailed results.

Moreover, the results of this study can be used to infer some practical implications. First, the entrepreneurs planning to establish an organization and become part of a complex network can analyze their positions, strengths, and weaknesses in the light of our study results so as to make more proper decisions about their activities. Our findings show that links with large-scale enterprises in relevant industries are important for emerging organizations in order to provide the necessary resources for survival and information to deal with uncertainty. Furthermore, organizations that have relationships with companies in complex networks can estimate their future relationship levels by using the findings of our study. Also, organizations with decision-making positions in complex networks, such as technology parks, may use the study results for long-term and short-term strategies since the data will help them to anticipate their chances of survival and success in complex networks.

Our findings also provide social implications. New organizations play important roles in society, such as creating new jobs and promoting social mobility (Carroll and Hannan, 1999), but also developing new technologies and driving economic growth (Dobrev and Barnett, 2005). With the survival and success of new organizations, related sectors can become healthier and safer, resources can be used correctly, and waste can be avoided, thereby contributing to the general social welfare. These study findings may serve as a guide for potential entrepreneurs who seek to start a business in a complex network.

Nevertheless, this research has some limitations. The most significant limitation is the number of respondent companies. Further limitations stem from companies' reluctance to answer questions that reveal their network ties and declare unsuccessful results and failures due to confidentiality. Aside from that, companies that have gone bankrupt

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may be unable to be reached. Future work may focus on other technology parks or networks that have features similar to those we set for our study.

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