Survival Analysis of Organizational Network – An Exploratory Study

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Abstract. Organizations interact with their surroundings and with other organizations, and these interactions are critical for learning and evolution. To overcome the problems that they face during their existence, organizations must certainly adopt survival strategies, both individually and in groups. The aim of this study is to evaluate the effect of a set of prognostic factors (organizational, size, collaboration strategies, etc.) on the survival of organizational networks. Statistical methods for time-to-event data were used to analyze the data. We have used the Kaplan-Meier product-limit method to compute and plot estimates of survival, while hypothesis tests were used to compare survival times across several groups. In our study, we were confronted with one exploratory categorical variable, the strategy of the network, with a large number of levels. We have compared the corresponding survival curves through hypothesis tests, and we conducted a study that established three groups of strategies with the same risk or survival probability. Regression models were used to study the effect of continuous predictors and to test multiple predictors. Since violations of the proportional hazards were found for several predictors, accelerated failure time models were used to study the effect of explanatory variables on network survival.

Keywords: Accelerated Failure Time Model · Kaplan-Meier Estimator · Networks · Survival Analysis

1 Introduction

Organizations are adaptive at different levels of analysis: individually or as a group. In this work, we devote special attention to network formation and regard networks as new forms of organizations. To understand the interactions between firms and the different mechanisms of adaptation that include learning and evolution, we will use survival analysis, in particular to analyze the effects of a set of parameters (organizational density, size, and age) on the founding and mortality of organizations.

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O. Gervasi et al. (Eds.): ICCSA 2023 Workshops, LNCS 14112, pp. 117–128, 2023.
https://doi.org/10.1007/978-3-031-37129-5_10

An inter-organizational network is a set of firms that interact through inter-organizational relations [1]. Johanson and Matsson [2] describe the network as a system of relationships based on a division of work in the network. The notion of an inter-organizational network is applied to a wide variety of relationships among organizations. The concept of inter-organizational networks can be applied to joint ventures, strategic alliances, industrial districts, consortia, social networks, and others. Hakansson [3, 4], Hakansson et al. [5], and others have studied the importance of relationships and learning in networks, making important contributions to the study of inter-organizational networks. Some authors study certain properties of the network structure that are interesting to analyse. One of them is the small-world effect, which was brought to the field of economics by many researchers such as Watts and Strogatz [6], Csermely [7], Latora and Marchoiri [8], etc. Watts and Strogatz [6] have shown that the connection form of some biological, technological, and social networks is neither completely regular nor completely random but somehow stays in between these two extreme cases. This type of network is named Small Worlds in analogy to the concept observed in social systems by Milgram [9]. Small-world networks are typically highly clustered, like regular matrices, but have a low path length, like random graphs. These properties are of great importance in economics. The work of Leskovec et al. [10] confirms what was said about the low path length of the small-world networks. In their work, graphs densify over time (i.e., the number of nodes increases), and at the same time the average distance between nodes decreases. The diameter of small-world networks decreases as well over time. We distinguish three main forms that characterize the most common processes of cooperation: linear, star, and multipolar networks. In a linear network (Fig. 1, top), each of the nodes of the network is connected to two other nodes. All the flow that is transmitted between nodes in the network travels from one node to the next node in a linear manner. In this case, activity A1 is managed by firm a1, activity A2 is managed by a2 and so on. No direction of the flows is identified in this graph, although the flow of resources can be unidirectional or bidirectional between nodes. Examples of this type of sequential network correspond to situations where firms collaborate with partners that are geographically close instead of searching for other networks that are already in action. The star network form (Fig. 1, left side) corresponds to the type of network form in which each of the nodes of the network is connected to a central node. Usually, firms rationalize resources and optimize activities when they form this configuration. The sharing of new technologies by a particular organization and the common benefit of resources are the main advantages of these topologies. Here the flows can also be bidirectional because the sharing of resources is not centralized but spread among the nodes of the network. Firms exchange, store, or get resources via the central activity A. In many situations, new firms are created to aggregate the activities of A: in this case, firm a5 contains activity A. One example of a network that follows this form is the grouping of suppliers. In this situation, firms are organized around a common client (usually a large client). This form of organizational network represents an interesting opportunity for the cooperating firms to organize their supplies more efficiently. In such a situation, the central activity is the goal of the network and constitutes the connection to the final client. The complementarities of the firms' competences are the key to the

set of relationships that motivate this type of network, which is based on complementary vertical relationships. Among the several advantages that firms can take from these groups of suppliers, we can emphasize cost reduction, access to new markets, and risk reduction in the development of new products. The clustering of several organizations characterizes the multipolar network form (Fig. 1, right site). Typically, the relationships between organizations belonging to the same cluster are strong, but those between organizations that belong to different clusters are weak (although the relationships in this latter situation are stronger than those with any organization that is outside the network). This kind of network is typical of the automobile manufacturing sector, although it can also be found in other industries, as, for instance, in the textile and clothing industry.

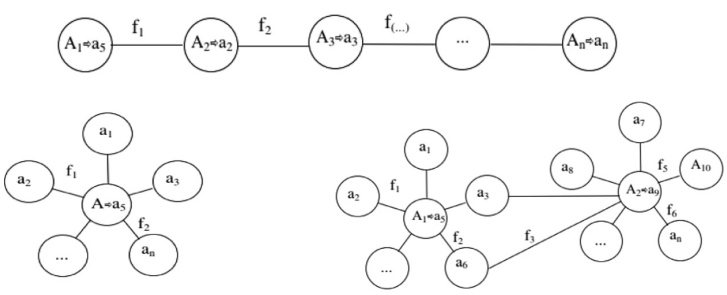


Fig. 1. Representation of the simplified forms of networks: linear network (top), star network (bottom, left side), and multipolar network (bottom, right side). Legend: ai denotes the individual agents or firms in the network; Ai denotes the cooperating activities (integrated into firms); and fi denotes the flow of resources (no direction of the flow is represented).

Firms typically join forces after adopting multiple cooperative strategies. According to Hitt et al. [11], a network cooperative strategy covers situations where several firms agree to form multiple partnerships to achieve shared objectives. Doing better than competitors (through strategic execution or innovation) and merging and acquiring other companies are the two primary means by which firms develop a cooperative strategy. Following Hitt et al. [11], cooperative strategies represent one of the major alternatives firms use to grow. Besides the network form (linear, star, or multipolar), the collaborative strategy adopted considers the following main variables of analysis: profit, stock of knowledge, marginal cost, and some other variable concerning network statistics (number of networks, nodes, etc.), at the firm or network level. These variables were collected for each strategy. The presence of the binary variable status (taking the value 1 if the network is alive at the end of follow-up and 0 otherwise) makes the use of survival analysis the appropriate statistical methodology for analyzing the survival time of the network (Age). Survival analysis will be used to study the distribution of lifetime as well as to compare the survival of two or more groups. Survival regression models will be used to study the relationship between life time distribution and explanatory (covariate) variables associated with each network. In order to be able to analyze the importance of these variables on the survival of the networks, data on inter-organizational networks is needed. It is possible to know how many firms are born and die every year according to the number of firms that exist in the same year. Therefore, it is possible to compute the

organizational density and measure its impact on actual organizational birth and death (contemporaneous density). Nevertheless, it is very difficult to analyze the impact of the founding density (the density at the time of founding) for a particular firm. For that, we should have real time series from which we could capture information for every firm. That way we could follow firms during their lifetimes. Information should contain several time periods for the same firm and also cover many observations corresponding to different firms. The formation of networks also requires much information. Surveys can be implemented, in which we could collect data about the types of relationships and the reasons that force firms to link to networks. To analyze the evolution of the network, several time points would be needed, and therefore several interviews should be conducted. The shape of networks is also very dynamic, and reality would be difficult to measure by the mean of surveys. It is also important to introduce different scenarios concerning the economic situation to analyze its impact on the evolution of firms and networks. For the reasons presented above, we have chosen to use simulation. Simulation is a simplification of the world, and a well-recognized way of understanding it. It provides tools to substitute for human capabilities and the possibility of implementing different scenarios by constructing a virtual economic world. In this case, we use micro simulation, where world events are driven by agent (firm) interactions. Emergent behavior of aggregate variables is then captured, and the parameters can be reformulated in order to simulate different scenarios coming from different socio-economic perspectives. More information about the simulation methods used to model the interactions between organizational networks can be found in a related publication by one of the authors [12]. This source provides additional details of the rules that govern the network interactions and the assumptions made in the simulation process.

2 Survival Analysis of Organizational Network

This section analyzes how a set of explanatory variables influences the survival of organizational networks. Survival analysis is the appropriate tool to model the lifespan of organizational networks.

In this study, simulated data from a set of 500 companies is studied from birth until death or the end of the study. The response variable is the age at which the company ‘died’. At the end of the study, 122 companies were still active (i.e., ‘alive’), while 378 had ‘died’. This means that we have 24.4% of right-censored observations in our data set. Besides the age or duration of life of the company, we have several explanatory variables that will be used to model the duration of life of the network. Tables 1 and 2 present a short statistical summary of these variables.

Table 1. Distribution of the categorical variables.

Categorical variables	N (%)	Censored (%)
Final status (status)		
0: alive	122 (24.4)	
1: dead	378 (75.6)	
Form of the network (form)		
1: when the shape is linear	352 (70.4)	92 (26.1)
2: when it is a single star	111 (22.2)	26 (23.4)
3: when it is a multipolar star	37 (7.4)	4 (10.8)
Collaboration Strategy (Strategy)		
A	56 (11.2)	18 (32.1)
B	94 (18.8)	18 (19.1)
C	51 (10.2)	22 (43.1)
D	58 (11.6)	8 (13.8)
E	56 (11.2)	12 (21.4)
F	82 (16.4)	20 (24.4)
G	49 (9.8)	10 (20.4)
H	54 (10.8)	14 (25.9)

Table 2. Mean and standard deviation for the scale variables.

Variables	Mean (SD)
Age (in years) (age)	4.914 (4.534)
Profit (in currency units) (profit)	9.421 (4.457)
Marginal Cost (in thousands euros) (mcost)	0.022 (0.023)
Number of existing networks at the time of its birth (netbirths)	1.604 (0.675)
Number of existing networks at the time of its death (netdeaths)	1.688 (0.709)
Number of existing nodes (firms) at the time of its birth (nodebirths)	6.708 (4.091)
Number of existing nodes (firms) at the time of its death (nodedeaths)	6.266 (3.891)
Stock of knowledge in Market X (stock1)	8253.5 (31144.9)
Stock of knowledge in Market Y1 (stock2)	17.163 (126.966)
Stock of knowledge in Market Y2 stock3	157.573 (1467.427)

3 Estimation of Survival

Empirical estimation of the survival function can be obtained using the Kaplan-Meier estimator [13], also known as the product-limit estimator. The Kaplan-Meier estimator is the most widely used method to estimate the survival function. It is a nonparametric estimator that computes the probability of observing the event of interest at a certain point in time, conditional on its survival up to that point. Figure 2a shows a graphical representation of the Kaplan-Meier estimator of survival for the lifetime of the organizational network. The corresponding curve shows the estimated survival probabilities against time. As shown in Fig. 2a, the survival function may not reach a value of 0 if the latest (largest) observations are censored. The Kaplan-Meier estimator can also be used to compute the median survival time, which is the time by which the probability of survival is 0.5. The median survival time can be appropriately estimated from the Kaplan-Meier curve as the x-axis (time) that crosses the horizontal line at 50% survival probability on the y-axis. According to this method, the network median survival is equal to 4.

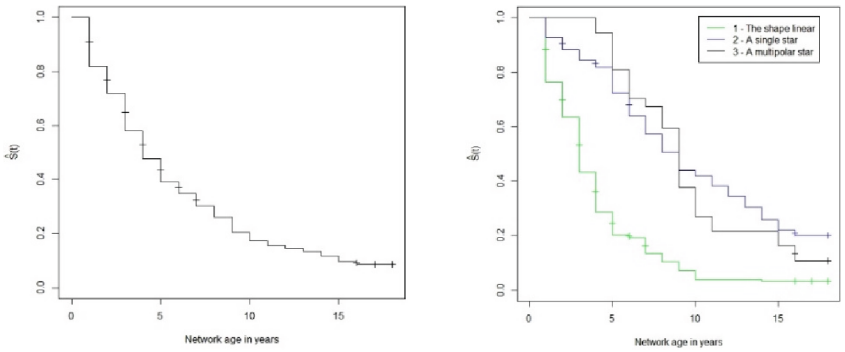


Fig. 2. (a) Kaplan-Meier estimator of survival; (b) Kaplan-Meier survival curves for each level of the covariable form.

Discrete covariates can be included in the Kaplan-Meier estimator by splitting the sample for each level of the covariate and applying the Kaplan-Meier method for each subsample. This is illustrated in Fig. 2b and Fig. 3a for variables form and Strategy, respectively. It is obvious from the analysis of Fig. 2b that those firms in a linear network (form = 1) have poorer survival than those classified in a single star network (form = 2) or a multipolar star network (form = 3). Table 3 reveals this issue too through the estimates of survival at 1, 3, 5, and 10 years since birth. Less differences can be appreciated when comparing the survival curves for form other than 1. In fact, it can be seen in Fig. 2b but also in Table 2 that the two curves cross. The median survival for firms in a linear star network is equal to 3, where those values increase to 9 for those in a single star network and multipolar star network.

Table 3. Kaplan-Meier survival estimates at 1, 3, 5, 10 and 15 years for each level of form and Strategy.

Categorical variables	1	3	5	10	15
Form					
1: The shape linear	0.764	0.434	0.204	0.039	0.031
2: A single star	0.928	0.846	0.724	0.420	0.220
3: A multipolar star	1.000	1.000	0.811	0.270	0.162
Strategy					
A	0.964	0.528	0.192	-	-
B	0.638	0.507	0.461	0.315	0.170
C	0.882	0.673	0.495	0.155	0.103
D	0.517	0.369	0.369	0.259	0.148
E	0.964	0.673	0.404	-	-
F	0.878	0.579	0.348	0.174	0.104
G	0.980	0.741	0.360	-	-
H	0.852	0.627	0.418	0.177	0.048

In Fig. 3a, we present the estimated probability of survival for each of the levels of the covariable strategy (Strategy) using the Kaplan-Meier estimator. In order to know if the survival of the organizational network can be influenced by the strategy, one can use a formal test to compare the survival distributions of the 8 samples. Under the assumption of proportional hazards, the log-rank test is optimal for testing the null hypothesis of equal survival distributions. However, as for covariable form, this assumption also seems to be violated for the covariable Strategy since several survival curves cross each other. Moreover, a test of the proportional-hazards assumption [14] indicated that the assumption is indeed violated in this case ($X^2 = 108.837$, $P = 1.6 \times e{-}20$). Under non-proportional hazards, log-rank is no longer the most powerful test [15]. The Peto & Peto [16] modification of the Gehan-Wilcoxon method [17, 18] can be a good choice in this case since it gives more weight to events at early time points. Results for the two methods (log-rank test and the Gehan-Wilcoxon test) are shown in Table 4 revealing that they can lead to different conclusions.

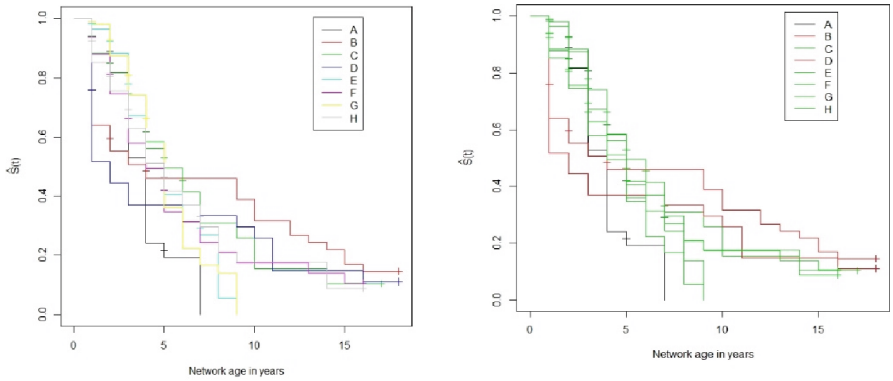
Table 4. Tests for comparison of survival curves.

Variable	Log-rank		Gehan-Wilcoxon	
	X^2 (df)	p-values	X^2 (df)	p-values
Form	110 (2)	$<2 \times e{-}16$	108 (2)	$<2 \times e{-}16$
Strategy	8.8 (7)	0.3	14 (7)	0.05

Table 5. P-values for the pairwise comparisons based on Peto & Peto test with corrections for multiple levels using the method proposed by Benjamini and Hochberg [19].

	A	B	C	D	E	F	G
B	0.619	-	-	-	-	-	-
C	0.196	0.308	-			-	-
D	0.061	0.308	0.061	-	-	-	-
E	0.066	0.619	0.780	0.061	-	-	-
F	0.619	0.619	0.619	0.061	0.619	-	-
G	0.061	0.619	0.780	0.061	0.986	0.619	-
H	0.585	0.619	0.649	0.078	0.780	0.780	0.789

Assuming the conclusion given by the Gehan-Wilcoxon test that at least one of these curves is different from the others, a naïve approach would be to perform pairwise comparisons. Results presented in Table 5 show the p-values from these comparisons with corrections for multiple levels using the one proposed by Benjamini and Hochberg [19]. The 8 groups lead to 28 pairwise comparisons with some p-values close to significance, in particular those involving groups 1 and 4, which correspond to the strategies A and D. When confronted with a considerable number of curves, one important question that tends to arise is if it is possible to group the curves in some manner. To this end, we have applied the methodology proposed by Villanueva, Sestelo and Meira-Machado [20], which allows us to ascertain whether these curves can be grouped or if all these curves are different from each other. Results from this methodology reveal the presence of three groups (i.e., strategies) with a similar survival pattern: Group 1 (A), Group 2 (B and D), and Group 3 (C, E, F, G, and H). The assignment of the curves to the three groups can be observed in Fig. 3b.



(a) **(b)**

Fig. 3. (a) Kaplan-Meier survival curves for each level of the covariable *Strategy*; (b) Estimated survival curves for each of the levels of the variable "Strategy". A specific color is assigned for each curve according to the group to which it belongs (in this case, three groups).

4 The Accelerated Failure Time (AFT) Model

The Cox proportional hazards model [21] is the most commonly used method for investigating the effect of explanatory variables on survival. A key assumption of the Cox regression model is that the hazard curves for the groups of observations should be proportional and should not cross. There are several graphical methods for identifying this violation, but the simplest is an examination of the Kaplan-Meier curves, such as those depicted in Fig. 2b and Fig. 3a. A more formal test was introduced by Grambsch and Therneau [14]. When there is clear evidence of nonproportional hazards, one should look for an alternative approach. Since the Accelerated Failure Time (AFT) models [22, 23] do not exhibit proportional hazards, they can be considered as a good alternative to the Cox proportional hazards model. The AFT model describes a situation where the biological or mechanical life history of an event is accelerated (or decelerated). The hazard function of the AFT regression model can be written in the following form:

$$h(t|\boldsymbol{X}) = h_0\Big(t\, exp(-\beta^T \boldsymbol{X})\Big) exp(-\beta^T \boldsymbol{X})$$

where X is a vector of explanatory variables, β is a vector of regression coefficients and $h_0(\cdot)$ is a baseline function of t, X and β. Under the AFT model, the effect of the explanatory variables on the survival time is direct, accelerating or decelerating the time to death or failure.

The survival distribution for the AFT is given by

$$S(t|\boldsymbol{X}) = S_0\Big(t\, exp(-\beta^T \boldsymbol{X})\Big)$$

where $S_0(t)$ denotes the baseline survival function. The factor e^{β} is called the accelerated factor. This factor is the key measure of association obtained in the AFT model that can be used to evaluate the effect of predictor variables on survival time. Suppose we are considering a comparison of survival functions among two treatment groups. Then, the probability of surviving time point t in the treatment group is similar to the probability of surviving time point $te^{-\beta}$ in the control group.

The log-logistic and log-normal regression models are two of the most common examples of accelerated failure time models. The exponential and Weibull parametric regression models can be considered AFT models too. In our analysis, we considered several AFT models. Table 6 shows the models and the corresponding values for Akaike's Information Criterion (AIC), which led us to choose the AFT model with log-logistic distribution as the best model.

Table 7 shows the results for the univariable and multivariable log-logistic regression models. The interpretation of the parameter estimates shows us the impact of each prognostic factor on survival. A positive coefficient indicates higher survival times for the organizational network. For example, the coefficient for "form – single star" is 1.090, which indicates that the 'survival times' for organizational networks in this group are extended by a factor of 2.97 compared to those in the group "form – shape is linear". Similarly, it can be seen that the survival times are extended with an increase in the variables profit and stock1. On the other hand, a one-unit change in netbirths shortens survival time by a factor of 0.538.

Table 6. Akaike's Information Criterion values under different survival distributions for multivariable parametric survival regression models with covariates form, strategy, profit, netbirths, stock1 and stock2.

Parametric Survival Model	AIC
Exponential	2015.968
Weibull	1898.177
Log-normal	1847.173
Rayleigh	1928.973
Log-logistic	1842.017

Table 7. Univariable and multivariable Log-logistic survival regression models.

Covariable	Simple regression		Multiple regression	
	$\hat{\beta}$	P-value	$\hat{\beta}$	P-value
Intercept	-	-	1.310	$<2.0 \times e{-}16$
Form				
1 – shape is linear	-		-	-
2 – single star	1.090	$<2.0 \times e{-}16$	0.997	$<2.0 \times e{-}16$
3 – multipolar star	1.126	$<2.0 \times e{-}16$	1.170	$<2.0 \times e{-}16$
Strategy				
A	-	-	-	-
B	-0.009	0.963	-0.511	$1.7 \times e{-}04$
C	0.281	0.156	0.096	0.524
D	-0.459	0.019	-0.897	$6.7 \times e{-}10$
E	0.226	0.205	-0.190	0.166
F	0.110	0.515	-0.156	0.241
G	0.229	0.208	-0.310	0.026
H	0.164	0.382	-0.361	0.010
profit	0.050	$5.5 \times e{-}06$	0.031	$5.1 \times e{-}04$
mcost	-5.488	0.0039		
netbirths	-0.619	$< 2.0 \times e{-}16$	-0.211	$5.1 \times e{-}04$
netdeaths	-0.323	$1.5 \times e{-}06$		
nodebirths	-0.016	0.190		
nodedeaths	-0.034	0.008		
stock1	$2.88 \times e{-}05$	$1.8 \times e{-}06$	$1.4 \times e{-}05$	$7.2 \times e{-}04$
stock2	0.006	0.002	$1.61 \times e{-}03$	0.176
stock3	$4.3 \times e{-}04$	0.081		

5 Conclusions

A set of methods were used for analyzing the lifetime of organizational networks. The Kaplan-Meier method estimates the probability of surviving beyond a certain time point and uses a hypothesis test to compare survival curves between different groups. For categorical variables with a large number of levels, we have used newly developed methods by the author that can be used to establish groups of networks (levels of the variable) with the same risk or survival probability. Graphs for the estimated survival curves revealed that the survival curves for groups of observations crossed each other, revealing nonproportional hazards. More formal tests confirm this issue, revealing that the well-known and widely used Cox proportional hazards model is not recommended to study the effects of the exploratory variables through regression studies. Accelerated failure time models based on different distributions were compared, revealing that the log-logistic regression model was the one with the lower value for Akaike's Information Criterion.

Authorship and Contributions. Luís Meira-Machado and Paula Lopes were involved in the analysis of the survival data whereas Pedro Campos was mainly involved in the data preparation and brought different expertise to the project in the particular area of application. Gustavo acted as corresponding author and will take primary responsibility for presenting the work and communicating with the journal and the reviewers. He also participating in the last revision and rewriting of the paper.

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