Modeling Organizational Integration using Mixing Patterns

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Abstract. *The analysis of mixing patterns in a social (or organizational) network, yields the laws of how nodes in a network connect with each other. We hypothesize that organizational networks with compatible mixing patterns will be integrated more successfully. We design a simulation experiment of organizational integration and show how mixing patterns and network assortativity affect the outcomes. The proposed method might be usefull in organizational mergers and acquisitions.*

Keywords. organizational integration, social network analysis, mixing patterns, assortativity, organizational design, simulation

1 Introduction

Mergers and acquisitions (M&As) are relatively new organizational forms through which companies try to protect or enforce their competitive position. Mergers comprise the integration of two or more organizations into a new entity or holding company. An acquisition is the acquirement of shares or property of some company in order to gain control over it [1].

The success of mergers and acquisitions is one of the fundamental questions many organization theorists and practititioners have worked on. The literature puts a great accent on the process of due diligence which is the process through which a potential acquirer evaluates a target company or its assets for acquisition [2, p. 252]. This process mostly concentrates on measurable figures like estimation of inventory and contracts, financial options, implications on the balance sheet, existing work contracts, supplier contracts as well as figures concerning products and their distribution. Such analyses often do not include an assessment of the human resources of the acquired entity (organizational knowledge, technical capabilities, creativity, experience etc.). Only more advanced understandings of due diligence activities include an evaluation of corporate culture and organizational compatibility.

An assessment of the human capital is often conducted just after the contract has already been signed, when the first integration problems appear. Under integration we understand the activities of harmonizing the organizational structure, business processes as well as objectives of the merging firms. Failure to integrate due to incompatible cultures is the most common reason for failed mergers and acquisitions [3].

A previous investigation on organizational characteristics as well as an evaluation of the new organization in the process of mergers and acquisitions, is an important step. Herein a formal approach for this step will be presented based on organizational network mixing patterns. We hypothesize that organizational social networks that have compatible mixing patterns will be integrated more easily then ones that don't. In order to prove this statement we will use a simulation experiment on two organizations with controlled characteristics which determine the outcome of a possible integration. These characteristics have their roots mainly in the spheres of organizational culture and human resources.

The objective of this research is thus to identify common laws in mergers and acquisitions, as well as prerequisites for success by using insights from social network analysis. We used the Watts-Strogatz algorithm [4] for generating social networks of two organizations. The algorithm was modified in order to reflect assortative mixing which we shall define further. The two networks were then integrated by using a new modification of the algorithm, in order to analyze the characteristics of the new (integrated) network.

2 Organizational Culture in Organizational Integration

Plenty of studies have shown that so called soft factors like organizational culture, play a major role in integration and seem to be one of the primary reasons for the high failure rates of mergers. After a literature review [5] concluded that there are two key factors with direct influence on mergers success: (1) compatibility of corporate cultures, and (2) cultural change management.

Likewise, a study by [6] showed that only 35% of over 500 considered M&As could be considered successful. Most important reasons for failure were: (1) ignoring people and culture, (2) slow integration, (3) lack of communication, as well as (4) failure to define roles, responsibility and structure precisely.

[7] contemplates that reasons for M&A failure are (1) non-adequate due-diligence, (2) value overestimation of the company to be acquired, (3) lack of rational strategy, (4) conflicting organizational cultures, and (5) slow integration.

A survey by Bain & Company [8] of 250 global executives involved in M&A, 61% identified "Problems integrating management teams" as a reason why deals break down. The only two factors which had a greater percentage were "Overestimated synergies' (66%) and "Ignored potential integration challenges" (67%). Furthermore, the study shows that 83% identified on-time cultural integration as a critical success factor [9, pp. 197–201]. Another study by Bain & Company [10] conducted over 125 mergers suggests that M&As where management proactively addressed culture had a higher average acquirer share price performance versus sector index, then deals in which companies failed to address cultural issues.

Harding & Rovit also identify culture in their M&A decision making principles grouped into the following categories: (1) ownership takeover plan, (2) fast integration where important, (3) setting culture at the peak of the management plan, and (4) maintaining the power of every-day business [9, pp. 108–111].

All these studies show that organizational culture plays an important role in M&As, which is why we will concentrate our efforts to establish a formal procedure for analyzing it and providing a model for decision making in M&As based on it.

3 Mixing Patterns

Every (social) network consists in principle of two parts: nodes and edges. Formally, networks are represented as mathematical graph structures which are the pair $G = (N, E)$, whereby $N = \{n_1, n_2, ..., n_m\}$ is the set of nodes, and $E = \{(n_i, n_j)|n_i, n_j \in N\}$ is the set of edges or arcs. If the pairs in E are arranged then G is a directed graph or digraph [11].

The type of a node is an arbitrary characteristic of some node. In a social network of people for instance, the node type can be some of the categories like sex, age, race, but also a network depended characteristic like the nodes degree. In our case we will assume that node types are artifacts as elements or organizational culture.

Mixing patterns define the way in which particular nodes connect. In the following we will concentrate on assortative mixing [12]. Assortative mixing with respect to given characteristic exists in a network if, on average, similar nodes connect. Likewise, disassortative mixing exists in a network if, on average, different nodes connect. If there is whether assortative nor disassortative mixing in a network, we say that the network is neutral, e.g. nodes do not choose other nodes with respect to the considered node characteristic.

A typical example of an assortative network is the network of collaborators in a functional organizational structure with respect to the characteristic of education and professional training, e.g. in an accounting department will most likely work accountants, while in the IT department there will collaborate computer specialists. On the other hand, a good example for a disassortative network can be a divisional organizational structure with respect to the same characteristic, e.g. every division will most likely have at least one accountant, at least one marketing professional etc. Hence, the criteria for collaboration is the diversity of professionals. To provide an example of a neutral network, any social network can be used that does not influence (or minimally influences) the linkage of nodes. Such a criterion is for example the eye color of participants in an e-mail communication network. The eye color of participants does not influence the selection of communication partners.

Assortative mixing is usually characterized with the quantity e_{ij} which measures the ratio of edges in a network which connect nodes of type i to nodes of type j. In undirected networks the quantity is symmetric in its indices, e.g. $e_{ij} = e_{ji}$. In directed networks this does not have to be the case.

Whereby in_i and out_i are the fractions of each type of end on an edge that is attached to node of type i. In undirected networks, where the ends of edges are all of the same type $in_i = out_i$. To measure the level of network assortativity one usually uses the assortativity coefficient [12]:

$$r = \frac{tr(\mathbb{E}) - ||\mathbb{E}^2||}{1 - ||\mathbb{E}^2||} \qquad (1)$$

where E is a matrix which elements are e_{ij}, $tr(\mathbb{X})$ is the trace of matrix X (the sum of the main diagonal in a quadratic matrix), and $||\mathbb{X}||$ the sum of all element of matrix X. The formula yields $r = 0$ when there is no assortative mixing (neutral network), since $e_{ij} = in_i out_i$. If the network is perfectly assortative the formula yields $r = 1$, since $\sum_i e_{ii} = 1$. If the network i perfectly disassortative, e.g. every edge connects two nodes of different type, then r is negative and has the value:

$$r_{min} = -\frac{||\mathbb{E}^2||}{1 - ||\mathbb{E}^2||} \qquad (2)$$

where r_{min} is in the interval $-1 \leqslant r \leqslant 0$. The value is not (as could be expected) equal to -1 since a perfectly disassortative network is closer to a randomly mixed network than is a perfectly assortative network. Especially in the case when there are more than 3 possible types of nodes, in a randomly mixed network, different nodes will connect more often.

Of special interest here are the dynamics of a network with respect to mixing patterns. To simulate networks various random network models are used [13]. One of such models, was developed by Watts and Strogatz [4] for generating social networks (as opposed to other types of networks). Since we deal with organizational networks, we will use this model for our simulations.

The original Watts-Strogatz algorithm (WS) starts off with a ring of N nodes, in which every node is symmetrically connected to its $2m$ nearest neighbors (m nodes in both directions). Then, for every node, edges connecting it are selected for redirection clockwise with a probability of p, or left intact with probability $1 - p$. If an edge is selected, it gets redirected to a random node in the network except for the one under consideration (reflexive edges – nodes linking to themselves – are avoided). In this way typically shortcuts to remote nodes in the network are established.

In the following we introduce two modifications to the WS algorithm, to reflect the needs of our simulation. The first alternation is due since WS doesn't allow us to generate networks with a given assortativity coefficient. Thus for every node n we introduce a arbitrary characteristic (denoted with $C(n)$) in order to generate a desirable mixing pattern. In addition to the probability p (represented with the random variable X_p), we introduce the probability q (represented with the random variable X_q) that determines the likenesses that two similar nodes (e.g. nodes with a same characteristic) will connect. Now, for an edge (n_1, n_x) to be redirected to (n_1, n_2), one of the following two conditions has to be satisfied:

$$p > X_p \land q > X_q \land C(n_1) = C(n_2) \quad (3)$$

$$p > X_p \land q \leq X_q \land C(n_1) \neq C(n_2) \quad (4)$$

The first condition is the situation when the network is assortative, and the nodes have the same characteristic (in an assortative network such nodes connect more often), and the second condition is the case when the network is disassortative, and the characteristics of the nodes differ. Using this modified algorithm (WSA), one can now flexibly generate random networks with an arbitrary assortativity coefficient by adjusting q as needed.

Both WS and WSA only redirect existing edges in order to remain the average degree of the network (e.g. the number of edges in the network is constant). Thus WS and WSA aren't suitable for the case when network dynamics have to be simulated (e.g. the establishment of new edges or the disappearance of existing ones). In the situation of merging two network, the establishment of new edges is of particular interest, which is why we introduce another modification to WSA: instead of redirecting edges, for each node new edges are established if one of the conditions from WSA is satisfied. In essence, the difference between this modified algorithm and WSA is that the to be redirected edges aren't deleted from the network.

If we now amalgamate two networks $G_1 = (N_1, E_1)$ and $G_2 = (N_2, E_2)$ as follows $G_A = (N_1 \cup N_2, V_1 \cup V_2)$ in order to establish only edges between the two networks which are integrated, we introduce another condition: for a new edge (n_1, n_2) to be established in G_A, it must hold that $n_1 \in N_1$ and $n_2 \in N_2$. We denote this new algorithm with WSAA.

4 Simulation

In order to conclude about our hypothesis we designed a simulation experiment of integrating two networks. Analyzed integrations were of sizes 10×10, 10×50 and 50×50 which can be seen as small to medium organizational units. A simulation was run for every combination of two networks for probabilities of connecting two similar nodes $q \in [0, 1]$ (step 0.1), and p was set to 0.1 for all simulations. The assortativity coefficient ranged from r_{min} to 1. Every network was designed to have three node types (X, Y, and Z) with a distribution of $(0.2, 0.3, 0.5)$ respectively. X, Y, and Z can be interpreted as characteristics that describe a given node (in the case or organizational culture artifacts). The nodes' characteristics distribution was generated so that every network had an average of 20 % nodes with characteristic X, 30 % with characteristic Y, and 50 % with characteristic Z.

Every network represents one organizational unit (department, group, organization etc.) for which one can say that it has a relatively homogeneous mixing pattern with respect to organizational culture. Nodes are individuals (employees) and edges are interpreted as linkages between them (collaboration, communication, mutual responsibility etc.).

Each run of the simulation had two phases. Firstly, the WSA algorithm was used to randomly generate two networks in a total of 200 intervals, whereby m was set to 3 and 10 for networks of 10 and 50 nodes respectively. Secondly, the networks were amalgamated and the WSAA algorithm was used to integrate them, again for 200 intervals. Every run was repeated 100 times to gather representative average data for the final (integrated) network. For each run we collected the weighted average ratio of new edges between the two networks weighted with the sizes of the participating networks (number of all edges in the integrated network / sum of edges in both networks before integration).

The simulation was implemented in Python[1] using the NetworkX[2] toolkit, and later analyzed in JMP.[3]

Figure 1 shows the ratio of newly established edges in dependency of the assortativity coefficient of the two integrating networks.

[1] `http://www.python.org`

[2] `http://networkx.lanl.gov/`

[3] `http://www.jmp.com/`

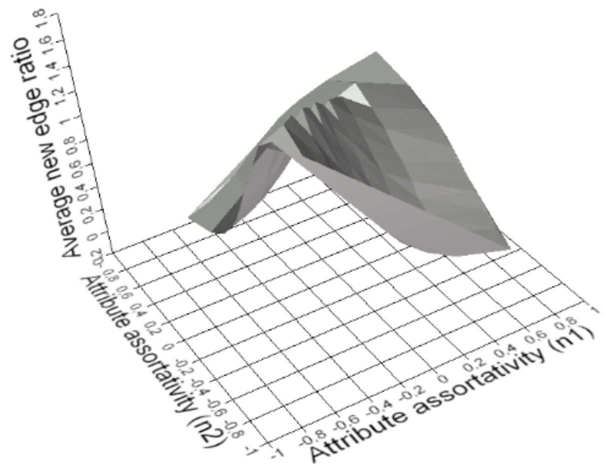

Figure 1. Average new edge ratio / attribute assortativity of integrating networks (integration 50×50**)**

As one can see, the greatest ratio of new edges gets established in the case of approximately identical assortativity coefficients. We consider that a newly established edge in the simulated networks should be interpreted as a predisposition for a linkage between individuals in a real integration. Individuals with similar assortativity are inclined to form a connection, but for a connection in a real M&A to succeed, the management of the newly established organization has to provide the formal prerequisites: structural, informational-communicational, transportation, and/or process related relationships. On the other hand, if the ratio of newly established edges is minimal, efforts for establishing cohesion are probably condemned to fail. In such a case the management should consider minimal integration or no integration at all.

5 Conclusion

The main presumption of this paper is that a good deal of M&As success depends on the particular organizational cultures of the organizations which are being integrated. One possible way to analyze organizational culture is through social network analysis, and especially mixing patterns based on artifacts as elements of culture.

The contribution of this work is given in the formal approach to M&A integration processes. We show how organizational integration can be modeled by using network assortativity. Characteristics that can be used to compute network mixing patterns can include demographics (age, sex, nationality, ethnic characteristics, etc.), culture (language, personal style, appearance, etc.), knowledge (profession, education, specialization, experience, etc.), reward systems (salaries, benefits etc.), and other types of criteria.

The hypothesis of the study was that networks which have a more similar mixing pattern will integrate more cohesively that those who haven't. In accordance with this hypothesis we designed a simulation experiment of integrating networks with selected levels of assortativity by using two new modifications of the Watts-Strogatz algorithm. The networks represented in the simulation can be any organizational unit: teams, departments, divisions, whole organizations or even networks of organizations. The analysis of the results confirmed the hypothesis: the more alike the mixing patterns are, the more cohesive the integrated network (more new edges, less attracting components).

The simulation model is limited in terms of simplicity (only one node characteristic is used for analysis; only two networks are analyzed in one integration). Our future research will focus on further investigation of this approach by using other possible metrics (like attracting components) as well as additional development of this method.

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