Strategic Positioning, Centrality and the Impact on Company Profitability

Tal Ben-Zvi*, Paul Rohmeyer** and Donald N. Lombardi ***

This study examines how strategic positioning in industry may predict a firm’s performance. Through simulation, we reveal that certain business positioning strategies correlate with eventual centrality and profit while other strategies correlate with isolation and poor performance. The paper also presents a novel classification method for centrality trajectories in industry, one that may be employed more generally as a predictor of industry change over time.

Field of Research: Strategic Management

1. Introduction

We know that centrality is associated with power in many situations, but we have yet to fully grasp how centrality emerges for some individuals or groups and not for others. In a business context, it is clearly advantageous for a company to be positioned centrally in a market of consumers and suppliers; however this clarity alone does not help us understand how some companies emerge as central.

Before electronics, centrality was inextricably linked to geography, as messages and goods traversed transportation networks. Now, in an age of electronic communication, messaging at the speed of light has led us to network models that are topological, in which distance is less important than connection. Thus, we can imagine companies as vertices in a network we call an industry. The prevalent model of network growth is preferential attachment (Albert & Barabási, 2002; Newman, 2001). The preferential model states that networks grow as newcomers attach to others in proportion to the amount of connections others already possess. That is, new entities attach to well-connected entities. But does this mean that centrality emerges only for companies that are well connected? Do companies just need to increase their number of ties?

This paper discusses the role of network theory in explaining company performance in a global business environment. When studying real industries, external factors like economic changes, industry size, number of competing companies, etc. may overwhelm other factors in determining the growth and change of the industry. Furthermore, it is quite difficult to compare between different industries or to compare companies within the same industry in different times along their life cycle.

One way to study strategic positioning within an industry and its impact on the individual company is to conduct a laboratory experiment. For that, we are using a business simulation that uses key the centrality notion to predict company performance. In detail, we

* Dr. Tal Ben-Zvi, Howe School of Technology Management, Stevens Institute of Technology, Hoboken, NJ, USA. Email: tal.benzvi@stevens.edu
** Dr. Paul Rohmeyer, Howe School of Technology Management, Stevens Institute of Technology, Hoboken, NJ, USA. Email: paul.rohmeyer@stevens.edu
*** Dr. Donald N. Lombardi, Howe School of Technology Management, Stevens Institute of Technology, Hoboken, NJ, USA. Email: donald.lombardi@stevens.edu
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use a laboratory approach to studying industries: we form teams of MBA students, and let them play roles as companies over a period of a year. The simulated companies form alliances, create contracts, and go bankrupt just as do real companies. The difference is that their interactions are recorded and can be analysed in detail, providing longitudinal data from a closed system. We use this environment to ask the following broad research questions: How does centrality emerge in industry? Are there strategies of behaviour that tend to lead to centrality or to isolation? Is centrality a function of individual company choice, or are the relations between companies the driving forces? And how does centrality relate to profit?

Findings reveal that centrality is indeed important, and that early choices can be made to predict subsequent network connectivity and profit. We show that there are strategies that correlate with eventual centrality and profit, and other strategies that correlate with isolation and poor performance.

The reminder of the paper is organized as follows: first, we review network theory literature. Then we set the study’s hypotheses and describe the employed methodology (the simulation). Next, we examine the implementation of network theory in the proposed simulation and analyse the hypotheses. Finally, we discuss the applicability of this study and draw conclusions.

2. Literature Review and Hypotheses

A key question in strategic alliances research is how the evolution of industries in which companies are embedded affects the companies’ behaviour, conduct, and profitability (e.g., Goerzen, 2005; Hite & Hesterly, 2001; Todeva & Knoke, 2005). Past studies typically analysed companies as autonomous entities, endeavouring for competitive advantage. These studies concentrated on either studying the external industry sources or the internal organizational capabilities and resources (see for example, Gulati et al., 2000). Nevertheless, past research does not address the positioning factor within the network and its consequences. Although company positioning within an industry is an external factor, firms have much control over it, even as the industry evolves or changes over time, by creating ties with other companies, for example. This paper aims to explore how entities (companies) may achieve a competitive edge by concentrating on their relationships with other entities within the industry network that they reside. We conduct this exploration by employing concepts from network theory.

One of the most studied concepts in network theory is the value of a position in a structure, now named social capital (e.g., Burt et al., 2001; Lin, 2008; White, 2004). Social capital is usually referred to as the contextual counterpart of human capital and refers to the value or the benefit that emerges from ties that an individual maintains with others. Furthermore, studies show that a lack of links between groups or individuals creates “holes” in the structure of the network (Greve & Salaff, 2003). Researchers state that these structural holes may represent an opportunity to control information and possibly bridge the gap between people or groups from opposite sides of the holes; and thus, create a competitive advantage for those who span them (Burt et al., 2001). We employ this concept to examine whether entities seize bridging opportunities between two or more communities to gain social capital. In short, we investigate whether such manoeuvring yields profits. To that end we explore the structure and the alliances of the network.
Among the several measures analysing the structure and alliances in networks is ‘network redundancy’ (see, for example, Scott, 2012). Network redundancy is an index that measures the existence of structural holes. It is frequently associated with the notion of centrality, corresponding to the intuitive notion of how well connected a vertex is within its environment (Carrington et al., 2005). This measure is also used to examine the absence or the underdevelopment of connections between different networks bound by culture, nationality or other common interests (Carrington et al., 2005). Applications of network redundancy may be found in Gilsing et al. (2008) who studied the innovation potential of firms’ alliance networks, and in Reagans & Zuckerman (2008) who examined network redundancy trade-offs.

This study proposes a new longitudinal network metric: The centrality trajectory. This measure is based on the network redundancy measure. We use the centrality trajectory to evaluate company collaboration during the early stages of the evolution of a network (industry). Specifically, we use this measure to explain how certain companies succeed more through their ties with other companies and are able to gain profits while other companies suffer from conflict and losses.

A company positioned better in the nascent stage may present better performance; however, early performance does not guarantee better performance in subsequent stages. With centrality trajectory, we not only measure the social capital of a single company at a certain stage, but we also examine how the company enhances or loses its social capital over time. Based on the previous status of a company and its current one, we define four main trajectory types: (a) Low Energy, a strictly below average connectivity; (b) Increasing Energy, a continuous increase in connectivity over time; (c) High Energy, a strictly above average connectivity; and (d) Declining Energy, a continuous decrease in connectivity over time. Figure 1 illustrates these four types.

**Figure 1. The Four Types of the Centrality Trajectory.**

To determine the trajectory type of a company, we need to define its level of connectivity with other companies. For that, we use transformations of network redundancy.

The network redundancy index measures the extent to which the ties of a company, represented by a vertex, are redundant, i.e., the extent that a vertex’s contacts are also connected to each other. We use this index to evaluate the redundancy of each vertex; that
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is, the ability of the network to continue its flow from one vertex to another after the vertex (and its adjacent edges) are removed (note that the network redundancy index relates to the F measure of fragmentation; see Borgatti, 2006 and Chen et al., 2006). To measure redundancy we modify Burt’s redundancy measure (Burt et al., 2001). The measure of redundancy for vertex $i$ in stage $t$, $a_{i,t}$, is defined as $1 - \frac{2 \sum r_{j,k,t}}{n(n-1)}$, where $r_{j,k,t}=1$ if vertex $j$ can reach vertex $k$ via any path of any length in stage $t$ when vertex $i$ is removed from the network, and $r_{j,k,t}=0$ otherwise. $n$ represents the number of vertices in the network.

When all remaining vertices are reachable from all the other vertices in stage $t$ as vertex $i$ is removed, then $a_{i,t}=0$. When all the remaining vertices are independent, $a_{i,t}=1$.

The centrality trajectory type of vertex $i$ is defined by the following ($\bar{a}_i$ is the average network redundancy in stage $t$ over all vertices):

$$
\text{Centrality Trajectory Type}_i = \begin{cases} 
\text{Low Energy} & \text{if } a_{i,1} < \bar{a}_1, a_{i,2} < \bar{a}_2 \\
\text{Increasing Energy} & \text{if } a_{i,1} < \bar{a}_1, a_{i,2} > \bar{a}_2 \\
\text{High Energy} & \text{if } a_{i,1} > \bar{a}_1, a_{i,2} > \bar{a}_2 \\
\text{Declining Energy} & \text{if } a_{i,1} > \bar{a}_1, a_{i,2} < \bar{a}_2 
\end{cases}
$$

Note that here we use the centrality trajectory to compare the network redundancy of each vertex to the average network redundancy only in the first two stages and determine the trajectory type of the each vertex accordingly. Thus, the first two stages are used to predict the final stage. Future research might examine how the accuracy of prediction might change with increasingly long trajectories.

Studies confirm that companies enter alliances to improve their competitive position (e.g., Gulati et al., 2000; Goerzen, 2005). Research also confirms a positive correlation between profits and networks with structural holes; that is, networks with less redundancy. For example, Burt et al. (2002) and Reagans & Zuckerman (2001) study the relationship between performance and market networks in US and foreign markets and industries. Burt et al. (2001) assert that the association between performance and network redundancy reveals the significance of structural holes and their ability to provide social capital.

Nevertheless, although the structure of a network and the characteristics of its vertices are vital to forecast its performance, the way through which the network characteristics affect performance is still unknown. We suggest that the centrality trajectory type of a company impacts its performance. Hite & Hesterly (2001) like Jack (2005) state that entities can obtain essential resources (for example, information) as a result of creating strong ties with other entities. Greve & Salaff (2003) and Steier & Greenwood (2000) argue that emerging networks enhance their search for new information by a large number of weak ties. Ludovici et al. (2009) compare different Networks-on-Chip switch architecture structures. They conclude that tightly integrated networks present better performance than loosely networks. Thus, hypotheses H1 and H2 propose examining how the centrality trajectory directly impacts performance:

**Hypothesis H1**: Companies classified as Low Energy or Declining Energy under-perform other companies.

**Hypothesis H2**: Companies classified as High energy outperform other companies.
3. Methodology

This study’s platform is a business simulation. Its objective is to offer participants the opportunity to learn by doing in as authentic a management situation as possible and to engage them in a simulated experience of the real world (e.g., Ben-Zvi, 2012). This usually enhances the characteristics of the simulation as a tool that reflects real life, and behaviour observed may be generalized to reality (e.g., Lainema & Makkonen, 2003). Simulations have been considered as a powerful tool to examine organizational phenomena (Harrison et al., 2007). Simulation is a method that can test that empirical results found in ‘the real world’ do not arise by chance.

We employ the International Operations Simulation Mark/2000. The simulation is highly realistic, meant to simulate the total environment. Participants were divided to teams (“companies”) and immersed themselves in an artificially created hi-tech industry, where companies conducted research, produced and marketed chips and PCs. The formation of the companies and allocation of executive roles within companies proceeded without external intervention or manipulation, and were reported to the simulation administrator before the simulation itself began. Running the simulation, each company could concentrate on any one or any combination of the functions of manufacturing, marketing of one’s own products or selling to overseas distributors, serving as a distributor or a subcontractor, exporting, importing, financing and licensing. The ultimate measure of company performance was the net profits each company achieved throughout the simulation.

The decision-making process in this simulation is based on an analysis of the company, interaction with other companies and the constraints stated in the player’s manual (e.g., procedures for production, types of marketing channels available). The simulation has become highly realistic as a result of the efforts invested in it to simulate the environment. It forces participants into a stream of top management decisions, typical of any large firm. Incoming participants play six simulated periods (“stages”) in each run. The length of each simulated stage is usually referred to as one year. Each run we started the simulation with new participants. Communication between companies can be made through email, phone calls, individual contact, or using two unique simulation features: (1) the simulation newspaper, where companies can advertise and look for partners; and (2) an electronic bulletin board created on the web with the ability to post electronic messages. Economic changes in the simulation are controlled by the administrator and communicated to the participants through the simulation’s newspaper. However, in our experience, those changes have very little impact on long-term gains or losses.

Overall, we conducted eight (independent) runs of the simulation with different participants in each run. A total of 602 students participated in this experiment. The number of participants in each run is detailed in Table 1. For this research, all the results are aggregated.

In all runs, the participants allocated responsibilities for specific functions, and worked to achieve common goals that they themselves defined. Our experience shows that executive roles were usually allocated according to the participants’ expertise in certain functional areas (e.g., accountants and bankers were usually assigned the role of chief financial officers). While each of them became a specialist in his or her function, a joint effort was required to pursue the common objectives of the company.
4. Findings

We analyzed the simulation as a network graph \( G = (V, E) \), characterizing the simulated companies as numbered vertices, where each vertex \( v \in V \); interactions between companies (e.g., licensing a patent or selling goods to another company) are represented by the edges, that is, \( <u,v> \in E \). Each link between two companies represents a trade transaction substantiated by a contract. Table 1 details the number of companies the participants operated in each run. As the table indicates, the number of companies in the industry varied from 10 to 20. On average, participants created about 17 companies.

<table>
<thead>
<tr>
<th>Run</th>
<th>Run I</th>
<th>Run II</th>
<th>Run III</th>
<th>Run IV</th>
<th>Run V</th>
<th>Run VI</th>
<th>Run VII</th>
<th>Run VIII</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Participants</td>
<td>44</td>
<td>90</td>
<td>90</td>
<td>74</td>
<td>72</td>
<td>68</td>
<td>90</td>
<td>74</td>
</tr>
<tr>
<td>No. of Companies</td>
<td>10</td>
<td>20</td>
<td>20</td>
<td>17</td>
<td>16</td>
<td>15</td>
<td>20</td>
<td>17</td>
</tr>
</tbody>
</table>

Figure 2 shows an example of the evolving network of relationships (i.e., the interactions between companies) in Run II. The left side of Figure 2 illustrates the industry after the first stage, whereas the right side of the figure shows the industry by the end of the simulation, after six simulated stages.

**Figure 2. Network structure in Run II; the left represents the beginning of the simulation, whereas the right corresponds to the end of the simulation.**

We now concentrate on the first two stages, and try to conclude the companies’ overall performance in the simulation (in the last simulated period) according to their early trajectory. Performance (as indicated above – a company’s net profits) was measured relative to the average company. We note that comparing absolute performance values may create a bias, as the industries evolved differently and a company that performed poorly in one run (i.e., did not produce a lot of profit) could be considered an average company in another run, where all companies competed fiercely and did not produce significant profits.

We classified each company in each run into one of the trajectory types according to the network redundancy index values in the first two stages of the simulation. In Table 2 we present an example from Run VI. We present the network redundancy index values of each vertex for the first and the second played period, i.e., \( a_{i,1} \) and \( a_{i,2} \). We also show the net profit of each company relative to the average company. Finally, we specify the trajectory type of each vertex.
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Table 2. Network redundancy, relative net profit, and the state of each vertex (company) in Run VI.

<table>
<thead>
<tr>
<th>Vertex (Company) No.</th>
<th>(a_{1,1})</th>
<th>(a_{1,2})</th>
<th>Relative Net profit</th>
<th>Vertex (Company) State</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.95</td>
<td>0.73</td>
<td>96.85</td>
<td>High Energy</td>
</tr>
<tr>
<td>2</td>
<td>0.90</td>
<td>0.53</td>
<td>-28.43</td>
<td>Declining Energy</td>
</tr>
<tr>
<td>3</td>
<td>0.95</td>
<td>0.67</td>
<td>52.72</td>
<td>High Energy</td>
</tr>
<tr>
<td>4</td>
<td>0.84</td>
<td>0.67</td>
<td>8.65</td>
<td>Increasing Energy</td>
</tr>
<tr>
<td>5</td>
<td>0.84</td>
<td>0.53</td>
<td>-33.68</td>
<td>Low Energy</td>
</tr>
<tr>
<td>6</td>
<td>0.90</td>
<td>0.41</td>
<td>-49.15</td>
<td>Declining Energy</td>
</tr>
<tr>
<td>7</td>
<td>0.84</td>
<td>0.67</td>
<td>8.58</td>
<td>Increasing Energy</td>
</tr>
<tr>
<td>8</td>
<td>0.84</td>
<td>0.53</td>
<td>-19.5</td>
<td>Low Energy</td>
</tr>
<tr>
<td>9</td>
<td>0.84</td>
<td>0.53</td>
<td>-66.87</td>
<td>Low Energy</td>
</tr>
<tr>
<td>10</td>
<td>0.84</td>
<td>0.41</td>
<td>-16.92</td>
<td>Low Energy</td>
</tr>
<tr>
<td>11</td>
<td>0.84</td>
<td>0.41</td>
<td>-31.18</td>
<td>Low Energy</td>
</tr>
<tr>
<td>12</td>
<td>0.90</td>
<td>0.67</td>
<td>64.68</td>
<td>High Energy</td>
</tr>
<tr>
<td>13</td>
<td>0.95</td>
<td>0.67</td>
<td>75.51</td>
<td>High Energy</td>
</tr>
<tr>
<td>14</td>
<td>0.84</td>
<td>0.53</td>
<td>-21.29</td>
<td>Low Energy</td>
</tr>
<tr>
<td>15</td>
<td>0.90</td>
<td>0.41</td>
<td>-39.97</td>
<td>Declining Energy</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>0.87</td>
<td>0.62</td>
<td><strong>0.00%</strong></td>
<td></td>
</tr>
</tbody>
</table>

Note the significant impact of structural holes on the network redundancy index. For example, for analytic purposes, if we removed company 3 from the network in the last played period of Run I, we would demonstrate the existence of structural holes. The removal significantly increases the network redundancy index from 0.38 (a relatively connected network) to 0.85 (a relatively loosely connected network); See also Figure 3 for illustration.

**Figure 3. Network Redundancy in Run I; the left represents the network in the last played period, while the right corresponds to the same network with the removal of company 3.**

Next, using the data from all runs, and using the trajectory types as dummy variables, we created a regression to predict the relative net profit (performance) of each company at the last simulated period of the simulation according to its trajectory type. Table 3 illustrates the coefficients associated with each trajectory type along with the regression’s F and p values.

The table reveals that a low energy company performed 35% worse than the average company (supporting Hypothesis H1). An increasing energy company performed just above the average company; High energy companies performed more than 100% above average (supporting Hypothesis H2); and finally, declining energy companies present a below
average performance of more than 50% (supporting Hypothesis H1). Given the significance of the regression, it appears that only high energy companies, maintaining their ties with other companies, tend to significantly outperform other companies; other companies struggle just to make the average net profit.

Table 3. Variables, F- and p-values for the regression according to the trajectory type index.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Energy</td>
<td>-35.9</td>
</tr>
<tr>
<td>Increasing Energy</td>
<td>4.3</td>
</tr>
<tr>
<td>High Energy</td>
<td>106.6</td>
</tr>
<tr>
<td>Declining Energy</td>
<td>-54.7</td>
</tr>
<tr>
<td>F-Value</td>
<td>20.3</td>
</tr>
<tr>
<td>p-Value</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

5. Discussion and Conclusions

This research used a simulation to augment knowledge on industry evolution. Although the general environment was mutual to all participants, the simulated companies became differentiated: each assumed a different strategy, different operating decisions, and a different approach to collaboration with other companies. And leaving the collaboration decisions to the companies resulted in a variety of relationships between companies (e.g., customers, suppliers, wholesalers, licensing companies). It appears that these relationships reflect most real life business approaches.

Beyond the creation of simulated industries, this study tested two hypotheses relating network characteristics and company performance. Our analysis provides broad support for both hypotheses. Overall, our findings indicate how variation in structure when a network emerges produces significant differences in company performance, contributing directly to an explanation of how and why centrality emerges.

Our results have implications for both researchers and practitioners. For the former, this study demonstrates the importance of studying network characteristics and their impact on the individual company. Nevertheless, researchers need to be cautious about using different network measures. While some measures may be correlated with performance, other factors do not present a direct impact. In addition, researchers should clearly specify what the exact nature of the measured variables is. Degree (the number of ties a certain vertex holds) and network redundancy, although related to network centrality, may exhibit entirely different phenomena.

The implications for practitioners are equally important. We found that simply examining the strategy used in the first two simulation rounds afforded predictive success in the last round. High energy strategies – that is, sustained centrality – predict success, and low energy strategies – that is, a tendency to isolation – predicts failure. The implication is clear: (1) redundancy that spans fewer structural holes leads to less social capital and lower profits; (2) spanning structural holes is the source of social capital and therefore presents high performance; and (3) network structure indicates both where social capital is distributed in the industry and where opportunities for collaboration (i.e., forming relationships) are located.
Pursuant to this research, companies that positioned themselves at the central, pivotal point of the industry early in the simulation and maintained alliances produced better performance. While this may seem retrospectively predictable, only about 20% of the companies actually implemented this strategy. The remaining companies either partially implemented these guidelines or ignored them all together; that is, there are many other strategies that the participants used: some have intentionally held back, trying to differentiate their company from the competition. Others lacked the ability to sustain partnerships and suspended their alliances in the hopes of better integrating their activities.

Yet, it seems that a single-minded focus on the entire industry is a promising business strategy. As an industry grows, more business ties are based on a calculation of economic costs and benefits. This makes the industry more intentionally managed industry where companies exploit structural holes. Therefore, companies wishing to enhance their profitability should: (a) establish and maintain partnerships and alliances; (b) construct them into an efficient network that grants access to diverse information and capabilities with minimum redundancy; and (c) prudently partner with potential rivals that offer more business opportunities and less risk of intra-alliance rivalry. Future research can examine whether those strategies are also valid in the real-world.

There is, however, a caveat: although simulations today present sufficient complexity to provide a realistic business setting, no simulation can replicate real-life industries. For example, in real-life markets, new companies are constantly formed. This contrasts the experimental environment to the extent that all companies formed simultaneously. Therefore, the relation of these finding to business practice must be examined with caution. As more data from real businesses become available, it will be easier to determine how simulated situations resemble reality. In addition, this study was conducted with students, which is a limitation by itself, as students do not necessarily present the characteristics of real company executives.

In a future study we wish to look more closely at the way initial alliances form. We learned from the experiment that the early stages of the simulation are crucial. Future studies might focus on the genesis of industries, structural holes and the emergence of social capital, and whether this genesis is the result of attributes of the company founders, or instead is random, and thus creates contingency.

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