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Organizational Design, Information Transfer, and the Acquisition of Rent-Producing Resources*

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Abstract

Within the resource-based view of the firm, a dynamic story has emerged in which the knowledge accumulated over the history of a firm and embedded in organizational routines and structures influences the firm's ability to recognize the value of new resources and capabilities. This paper explores the possibility of firms to select organizational designs that increase the likelihood that they will recognize and value rent-producing resources and capabilities. A computational model is developed to study the tension between an organization's desire to explore its environment for new capabilities and the organization's need to exploit existing capabilities. Support is provided for the proposition that integration, both externally and internally, is an important source of dynamic capability. The model provides greater insight into the tradeoffs between these two forms of integration and suggests when one form may be preferred over another. In particular, evidence is provided that in uncertain environments, the ability to explore possible alternatives is critical while in more certain environments, the ability to transfer information internally is paramount.

Keywords: organization design, dynamic capability, information diffusion and social networks

Students of business strategy have long sought to identify the sources of supra-normal firm profits, otherwise called "rents". Rents are returns in excess of those from alternative investments of similar risk. Resource-based theorists have proposed that rents result from firm level resources acquired through imperfect factor markets that allow a firm to implement favorable product market strategies (Lippman and Rumelt, 1982; Wernerfelt, 1984; Barney, 1986). Barney (1986) observed that imperfect factor markets arise when firms have different expectations about the future benefits of certain resources and capabilities. Differences in expectations are possible because of causal ambiguity between organizational actions and economic outcomes (Lippman and Rumelt, 1982) and information asymmetries between firms (Arrow, 1974).

While there has been considerable progress in identifying why certain resources once acquired may be a source of enduring competitive advantage (see Rumelt, 1987), only relatively recently has progress been made in identifying how firms acquire those resources in the first place. A dynamic story has emerged in which the knowledge accumulated over the history of the firm and embedded in organizational routines and structures influences the firm's ability to correctly value new resources and capabilities (Teece and Pisano, 1994; Dosi and Marengo, 1994; Cohen and Levinthal, 1990). At any point in time, the decision to acquire

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particular resources or develop new capabilities is constrained by the firm's history. In other words, the evolution of a firm's resources and capabilities is a path dependent process.

The importance of history has lead some to conclude that the possession of rent-producing resources is primarily a result of luck (Barney, 1986) or idiosyncratic differences at the founding of an organization (Porter, 1994). Others have proposed that the existence of rent-producing resources is an indication of a higher-level capability to identify valuable resources and capabilities (Teece and Pisano, 1994). Some firms are more skilled than others at recognizing and processing useful information and consequently are more likely to make good resource decisions over time.

A number of theorists have proposed that this higher-level, "dynamic" capability is related to the degree to which a firm integrates, both externally and internally, diverse constituencies possessing unique knowledge (Dosi and Marengo, 1994; Iansiti and Clark, 1994; Henderson, 1994). Behavioral and cognitive theorists have long observed that the ability of an individual to assimilate new information is largely dependent on prior related knowledge (Chase and Simon, 1973; Taylor and Crocker, 1981). Prior knowledge is represented in cognitive structures that are used to interpret new information signals. The more divergent a signal is from current cognitive structures, the more difficult it is to understand. On the organizational level, the ability to process information has been associated with the distribution of prior related knowledge residing in individual organizational members *and* the ability to diffuse information across these individuals (Cohen and Levinthal, 1990). The more connected organizational members are to diverse sectors of the outside world, the more likely they will be aware of and be able to assess the value of various resources and capabilities. The more connected organizational members are to each other, the more likely that this information will be communicated to relevant actors or decision makers within the organization.

Unfortunately, maintaining highly integrative structures is costly. Establishing diverse linkages to the outside world requires resources and effort. The more diverse these linkages, the more costly it is to maintain internal coordination and control. A natural tension is created between a desire to allow diverse exploration for new resources and capabilities and a desire to exploit the fruits of discovery (Dosi and Marengo, 1994; March, 1991). While greater exploration is achieved through more diverse organizational participants, exploitation is easier the more homogeneous organizational members. Control and coordination of diverse organizational members is difficult. People within the same firm may find it difficult to communicate effectively. Total integration is difficult because external integration undermines internal integration and vice versa.

Given the paradox of the "integrated" firm, is it possible to design organizational structures that increase the likelihood a firm will recognize, value, and capitalize upon potential rent-producing resources and capabilities but are not so costly that they completely undermine short-term efficiency? In this paper, I explore the benefits and costs of achieving integration through various organizational designs. To this end, I adopt an information processing view of the firm (Marschak and Radner, 1972; Galbraith, 1977; Tushman and Nadler, 1978; Burton and Obel, 1984; Carley, 1998). After briefly reviewing some classic work from this perspective, I develop a computational model of the acquisition and diffusion within a firm of information, or knowledge, that arises outside the firm. Analyzing the model, I find that, depending on the cost structure, achieving both external and internal integration is prohibitively costly. The best type of integration (external or internal) is dependent on the nature of the competitive environment.

1. Literature Review

Research into the influence of organizational structure on a firm's ability to process information has a long tradition in a variety of fields. In economics, an information processing view of organizations is adopted by Marschak and Radner (1972) in their theory of teams. Team theory assumes that in many situations it is efficient for firms to decentralize information processing, i.e., have multiple decision makers, and to decentralize the information itself, i.e., provide different sets of information to each decision maker. The goal of team theory is to determine the efficient decentralization of information in various decision-making environments (Radner, 1992). Pulling from computer science, team theorists have developed numerous models of efficient information processing networks. Work in this vein continues today with researchers using computational models as opposed to earlier, analytically tractable approaches (Miller, 1996; Stein and Bernard, 1996).

In sociology, diffusion theorists have proposed that a firm's innovativeness—the ability to recognize and adopt new technologies and practices as they arise—is related to the degree to which an organization is complex, specialized, and externally integrated (Zaltman et al., 1973; Baldridge and Burnham, 1975; Kimberly and Evanisko, 1981; Dewar and Dutton, 1986; Meyer and Goes, 1988). Contingency theorists have proposed that different organizational designs may be appropriate given the information processing requirements of the environment. For example, Burns and Stalker (1961) propose that more organic (i.e., flat or decentralized) organizational structures are preferable in dynamic environments that require a high degree of information processing. Lawrence and Lorsch (1967) echo these sentiments concluding that in uncertain environments greater differentiation is needed and necessitates less hierarchical forms of internal integration.

A number of organizational design theorists have taken a much more explicit information processing view. Allen (1977) proposes that various structural configurations, such as the use of gatekeepers, will encourage communication and information flows. Galbraith (1977) explores a wide variety of organizational mechanisms that foster internal information flows. Tushman and Nadler (1978) suggest that information processing may be used to integrate the organization design literature and develop a number of propositions along these lines. Information processing scholars have often adopted computational models to analyze the information processing abilities of various organizational designs (Cyert and March, 1963; Burton and Obel, 1984; March, 1991; Carley, 1998; Carley and Lin, 1997). Cyert and March's (1963) "A Behavioral Theory of the Firm" is a classic study of the effectiveness of various organizational structures that uses a computational model. Another example is Burton and Obel's (1984) use of a decomposed mathematical programming model to explore the influence of information on efficient organizational design.

One model of particular interest to this paper is March's model of organizational learning (March, 1991). March's model captures the tension between exploration and exploitation by modeling the evolution of beliefs individual agents hold about an abstract reality. Central to March's model is the importance of organizational codes that shape and are shaped by the beliefs of organizational agents. March finds that while engrained organizational codes help with short-run learning and efficiency they may also undermine long-run knowledge creation.

Also of interest, Carley's ORGHEAD model adopts a dual-level information processing structure (Carley, 1998). At the operational level, agents work on a set of classification tasks (Carley and Lin, 1997). Agents communicate and learn in the presence of differences in information access and cognitive limits to information processing. At the strategic level, a CEO makes adjustments to the organizational structure using a simulated annealing approach to alter structure (Carley and Svoboda, 1996). The CEO may choose the number of agents and the assignment of tasks to agents. Through a series of virtual experiments, Carley (1996) finds that the relationship between performance and various organizational designs is highly non-linear and that firms may become trapped on local optima. She proposes that the mere act of reorganization may help improve performance.

In the section that follows, I construct a model of the acquisition and diffusion within a firm of information that arises outside the firm. This model builds upon the insights and methods of the literatures discussed above in a number of ways. Common to most models of organizational design, the model contains a model of the agent, a model of the internal organization structure, and a model of the task (Carley, 1995). Agents are assumed to be cognitively limited in the sense that their current knowledge sets determine the ability to process information. Building on the social network literature (Burt, 1992; Krackhardt, 1994), the model uses an explicit graph representation of the interaction among agents in the organization. This allows us to look at some common measures of organizational structure such as size and density as it relates to the innovativeness of the organization. Finally, in contrast to models based on a classification task (e.g. Carley and Lin, 1997), the task of agents is to primarily learn about and communicate the existence of new innovations. In this way, the model provides a bridge between models of organization design with models of organizational learning (Lant and Mesias, 1992).

2. The Model

Imagine a firm consisting of (1) a top management team or chief executive officer who serves as the primary decision maker for the firm and (2) a set of subordinate organizational members, or agents, who engage in a series of routines or tasks to produce a given product or service. To simplify the model, assume that the firm operates in a non-differentiated, competitive market. The primary task of management is to assign agents to perform necessary tasks and design an organizational structure that specifies the flow of information, or coordination, between agents. We may refer to the assignment of tasks and structure as the *organizational design*. Associated with a given organizational design is a set of costs. These costs include the costs of securing the services of various agents, maintaining information channels, and coordinating agents to perform tasks. In the short term, the organizational design problem is to choose a structure that produces the given product or service at minimal cost.

Now assume that in this world new cost-saving innovations periodically arise. The continued survival of the firm depends on quickly identifying, properly valuing, and adopting these innovations. Failure to do so will lead to decreasing margins as competitors lower prices and produce at lower cost. As argued earlier, the ability of a firm to recognize, value, and adopt a particular innovation is largely dependent on the firm possessing prior knowledge of related technologies or practices. More specifically, the likelihood that an individual within the firm will recognize and value a particular innovation is dependent on his or her prior related knowledge.

Whether the firm adopts the innovation is dependent on the ability of knowledgeable individuals to communicate the innovation's existence and value to other members of the organization. To increase the likelihood of recognizing innovations as they arise, the firm invests in structures that increase both external and internal integration. In such a world, short-run efficiency is insufficient for long-run survival. In the long run, the organizational design problem is to select a structure that reduces cost *while* increasing the likelihood of adopting new innovations.

To illustrate, consider a firm (f) made up of a finite set of agents (A_f: a_1 ..a_N). Within the organization, agents are arranged in networks that specify the flow of information among them. I will refer to this information-processing network as the organization's structure (S_f). The organizational structure determines whether information may flow directly between any two agents. I assume that any one link is only unidirectional, e.g., information may be transferred from A to B but not B to A. For information to be exchanged both ways, two links are required. As with other directed social networks, the structure may be represented by a two-dimensional array bounded by the number of agents in the organization (Scott, 1991).

$$S_f(N, N) \quad \text{where } s_{ij} = 1 \text{ if a link exists and 0 otherwise} \tag{1}$$

Assume that each organizational agent possesses a unique history. They have received different education, training, and work experience. For example, firm members often classify themselves into various categories, e.g., engineers, managers, line workers, marketing. The association of organizational members within professions often greatly shapes their knowledge of the world. Based on these histories, organizational members possess certain knowledge sets. We may imagine that these knowledge sets may be mapped in some n-dimensional space. Any one agent only understands a certain region of the total knowledge space, i.e., no one knows everything. For modeling purposes, assume that agents may be positioned along a continuum such that the central tendency of their "knowledge" position falls in some range 0 to 1.

$$k_i \in (0, 1) \quad \text{for all agents } i = 1 \text{ to } N \tag{2}$$

Information residing along the continuum far away from an agent's central knowledge position is assumed to be difficult for an agent to comprehend. Thus, the likelihood that an agent discovers an innovation (I) that arises at a particular position on the knowledge continuum (k_I) is dependent on the proximity of the agent's central knowledge position to the innovations. Similarly the ability of any two agents to transfer information between themselves is dependent on the proximity of their central knowledge tendencies. I define the "mental distance" between any two agents or between any two points on the knowledge continuum as equal to the distance between their central knowledge positions.

$$d_{ij} = \min(|k_i - k_j|, |1 - k_i + k_j|) \quad \text{where } k_i > k_j \tag{3}$$

I assume that the probability of discovering an innovation directly, i.e., not from fellow organizational members, decays exponentially the farther the mental distance between the agent and the knowledge position of where the innovation arose. We may create an operation "∇" to represent the discovery of an innovation (I) by an agent (a_i). Alpha (α) and beta (β) represent parameters that specify the degree to which it is difficult to acquire information given a certain mental distance.

$$\text{Prob}(a_i \nabla I)_{\text{directly}} = \alpha \exp^{(-\beta d_{ij})} \tag{4}$$

I similarly assume that the probability of transferring information between any two adjacent agents—agents connected in the organizational structure by a direct path—decays exponentially the farther the mental distance between agents. I define the operation "$\rightarrow$" to represent the transfer of information between any two agents, a_i and a_j.

$$\text{Prob}(a_i \rightarrow a_j)_{\text{adjacent}} = \alpha \exp^{(-\beta d_{ij})} \tag{5}$$

We may calculate the probability of transfer between any *non-adjacent* agents (a_i and a_j) as equal to the joint probability of transferring between all adjacent agents (a_{a1} .. a_{am}) in the path between the non-adjacent agents. Note that if no such path exists, then the probability of transfer is zero.

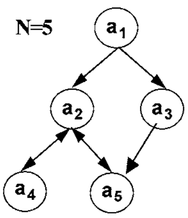
$$\begin{aligned}\text{Prob}(a_i \rightarrow a_j)_{\text{non-adjacent}} &= \text{Prob}(a_i \rightarrow a_{a1}) * \text{Prob}(a_{a1} \rightarrow a_{a2}) \\ &\quad * \ldots \text{Prob}(a_{am} \rightarrow a_j)\end{aligned} \tag{6}$$

Finally, we may calculate the overall probability of transferring information between any two agents connected by multiple paths as equal to the probability of transferring information along any of the various unique paths between agents given the organizational structure, S_f.

$$\text{Prob}(a_i \rightarrow a_j)_{\text{overall}} = 1 - \Pi_{\forall\text{paths}}[1 - \text{Prob}(a_i \rightarrow a_j)_{\text{path}}] \tag{7}$$

As an illustration, consider the hierarchical organizational structure in figure 1. For simplicity, assume that the information diffusion parameters, α and β, both equal one. In such an organization, the probability that agent two will successfully communicate some piece of information to agent five is approximately 63%. Likewise, the probability that agent four will successfully communicate some piece of information to agent five is given by the joint probability of transferring between agent four and two and agent two and five (~56%). Finally, the probability that agent one will successfully communicate some piece of information to agent five is given by the combined probability of transferring information via agent two or via agent three (~86%).

We may calculate the overall likelihood that an agent learns about the existence and value of an innovation as the probability the agent herself discovers the innovation and the



$$K_f = \begin{vmatrix} k_1 \\ k_2 \\ k_3 \\ k_4 \\ k_5 \end{vmatrix} = \begin{vmatrix} 0.82 \\ 0.01 \\ 0.52 \\ 0.12 \\ 0.48 \end{vmatrix} \qquad S_f = \begin{array}{c|ccccc} s_{ij} & a_1 & a_2 & a_3 & a_4 & a_5 \\ \hline a_1 & - & 0 & 0 & 0 & 0 \\ a_2 & 1 & - & 0 & 1 & 1 \\ a_3 & 1 & 0 & - & 0 & 0 \\ a_4 & 0 & 1 & 0 & - & 0 \\ a_5 & 0 & 1 & 1 & 0 & - \end{array}$$

Figure 1. An example firm structure.

combined probability that other agents discover the innovation and communicate information about this innovation to the agent.

$$\mathrm{Prob}(a_i \nabla I)_{\mathrm{overall}} = 1 - \prod_{j=1,N} (1 - \mathrm{Prob}(a_j \nabla I)_{\mathrm{directly}} * \mathrm{Prob}(a_j \to a_i)_{\mathrm{overall}}) \tag{9}$$

Thus, for any firm (f) and innovation (I), we may characterize the probability of the organization discovering an innovation as the average likelihood that any one agent discovers the innovation.

$$\mathrm{Prob}(I|S_f, K_f) = \sum_{i=1,N} \mathrm{Prob}(a_i \nabla I)_{\mathrm{overall}}/N \tag{10}$$

To be consistent with managers' organizational design decisions, we must recognize that associated with a given organization structure is a cost. I assume that cost is a function of the number of agents in the organization (N_S) and the number of communication links between them (L_S). The cost associated with the number of agents in the organization may be thought of as the compensation required to secure services, i.e., to align incentives. Communication costs include formal information systems as well as the time and effort required in less formal means of communicating. The total number of communication links associated with a given structure is equal to the sum of individual array elements ($L_S = \Sigma_{i,j} s_{ij}$). For the sake of simplicity, I assume that these two costs are separable and linear additive.

$$C_S = c_a(N_S) + c_c(L_S) = c_a(N_S) + c_c(\Sigma_{i,j} s_{ij}) \tag{11}$$

Associated with an innovation are the potential returns if implemented (R_I). In the simple model presented here, these returns are assumed independent of how many organizations adopt. One may imagine more complex models where returns are partially a function of the actions of other organizations. We may calculate a firm's profitability in any time period as the returns from an innovation conditional that the organization adopted the innovation minus the cost of the given organizational structure.

$$\pi = (R_I \mid I) - C_S \tag{12}$$

The probability that a firm discovers and implements an innovation of a certain type, k_I, is equal to the likelihood of discovering the innovation and the likelihood of an innovation of such type arising. The expected probability of adopting innovations in general can be determined by integrating across the entire knowledge space.

$$E[\text{Prob}(I)] = \int_{k=0..1} \text{Prob}(I \mid S_f, K_f) * \text{Prob}(I = k)\, dk \tag{13}$$

As a baseline, I assume that innovations arise stochastically and are uniform across the knowledge continuum. In other words, $\text{Prob}(I = k)$ is the same for all k.

Finally, I assume that organizations wish to maximize current profits, in other words, to maximize the expected returns from implementing innovations less the cost of maintaining a certain organizational form. The expected returns are equal to the expected returns from adopting an innovation conditional that the organization adopts the innovation. I assume organizations have no direct influence over where innovations may arise. Their choice variables are simply the selection and structuring of agents.

$$\max_{S,A} E[\pi] = E[R_I] * E[\text{Prob}(I)] - C_S \tag{14}$$

3. Analysis

To begin to illustrate the potential tradeoffs between various organizational designs, I calculated the expected likelihood of discovering innovations and the expected returns for three, prototypical organizational structures: a fully connected graph, a bi-directional circle, and a binary tree. Each is assumed to consist of five, evenly distributed agents. By "evenly distributed", I mean that the central knowledge tendency of the agents is evenly spread across the knowledge continuum. As to be expected, the fully connected graph conferred the greatest likelihood to adopt innovations should they arise (see figure 2). All else being equal, the high number of links in the structure make transfer of information between any two agents much more likely than less connected structures.

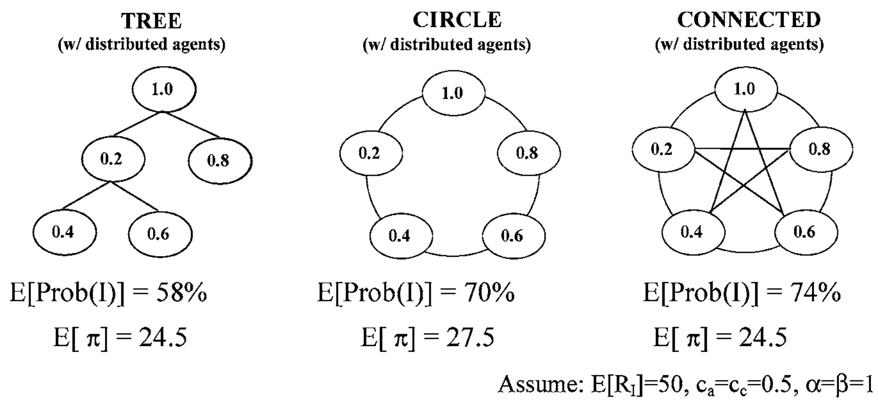


Figure 2. Comparison of common structures.

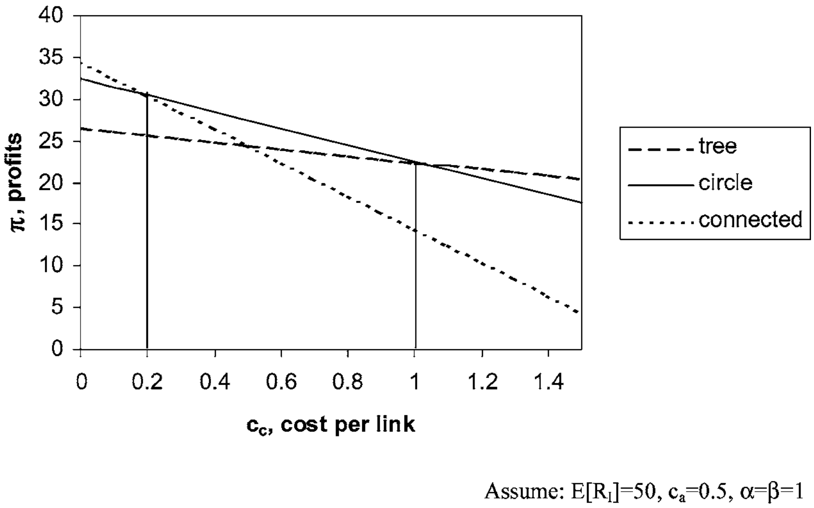


Figure 3. Preferred structures under different cost scenarios.

While the fully connected graph maximized expected adoption, it did not perform best as far as expected profits. This is due to the cost of maintaining an organizational structure with so many communication links. The reported expected profits in figure 2 are highly dependent on the assumed cost structure. Assuming a per link cost of 0.5, the circle conferred the highest expected profits. Given sufficiently low cost per communication links, the fully connected graph will perform best. Conversely, given sufficiently high cost per communication link, the tree will perform best. Figure 3 illustrates the change in relative profitability as the cost of communication links is increased given the assumptions in figure 2. At a link cost less than 0.2, the fully connected graph is preferred. For a link cost greater than 1.0, the tree is preferred.

Next, I estimated the impact on adoption of various distributions of agent knowledge positions for a given organizational structure, the fully connected graph. Using a base case with our discovery parameters (α and β) set to one, I found the somewhat unintuitive result that the distribution of agents had little effect on the expected probability of adopting innovations (see figure 4). To explore this phenomenon further, I adjusted the parameters so that the discovery of innovations by any agent was highly likely. In this case, I found that the expected probabilities converge—in this case to approximately 83%. Setting parameters so that the likelihood of discover was very low showed the greatest divergence—an almost doubling in probability for distributed over homogeneous configurations.

3.1. *Virtual Experiment*

Further inquiry revealed an interesting dynamic between the desirability of diverse agents and connected, or dense, organizational structures as the likelihood of discovery is varied. To illustrate this dynamic, a virtual experiment was run in which the likelihood of adoption was calculated for a set of randomly generated organizational designs under various parameter

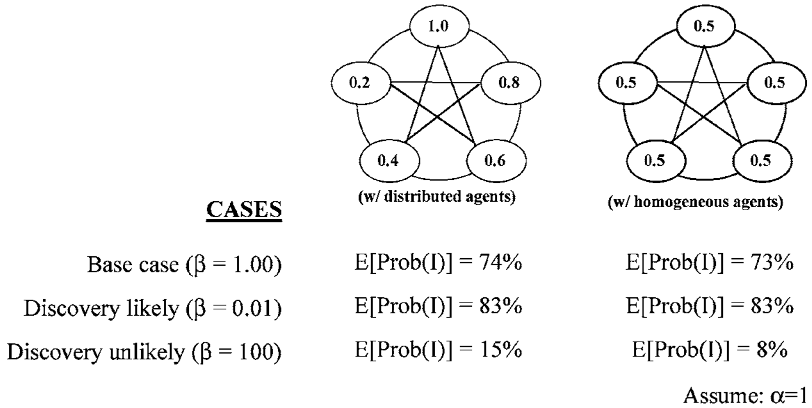


Figure 4. Comparison of distribution of agents.

specifications. Random values were assigned for the number of agents in the firm (N), the knowledge positions of those agents (K_f), and the linkages between agents. For the two information transfer likelihood parameters, α and β, I assigned one of three values representing high, low and medium likelihood (See Table 1). The experiment was repeated seven hundred times for each combination of α and β for a total of 6300 iterations.

Individual organizational designs are characterized by three measures. *Size* refers to the number of agents in the organization. *Density* represents the degree to which agents with the organizational structure are linked, or connected. Density is a common measure of network connectedness used in social network analysis (Scott, 1991). For directional networks, density is measured as the total number of links in the structure divided by the number of agents multiplied by the number of agents minus one.

$$Density = L_S/N_S(N_S - 1) \tag{15}$$

Diversity represents the degree to which agents' knowledge positions differ. I measure diversity as the variance of the distribution of central knowledge positions of the agents in the organization.

$$Diversity = \sum (k_i - \bar{k})^2/(N_S - 1) \tag{16}$$

Table 2 presents summary statistics from the experiment. The probability of a firm discovering an innovation (*Probability*) was calculated using Eq. (10). The average value of

Table 1. Tested values of parameters, α and β.

	High	Medium	Low
α	0.6	0.4	0.2
β	0.1	1.0	10.0

Table 2. Descriptive statistics and correlations.

Variable	Description	Mean	StD.	Min	Max	1	2	3	4	5	6
1. Probability	Likelihood of discovering innovation	0.44	0.35	0.02	0.99	1.00					
2. Density	Number of links over the number of possible links	0.46	0.06	0.15	0.77	0.03	1.00				
3. Diversity	Variance of agents' knowledge position	0.08	0.03	0.00	0.23	0.00	−0.01	1.00			
4. Size	Number of agents in the firm	21.93	25.06	5	95	0.30*	−0.01	0.03	1.00		
5. α	Likelihood of information transfer parameter	0.40	0.16	0.20	0.60	0.49*	0.02	−0.01	−0.03	1.00	
6. β	Likelihood of information transfer parameter	3.81	4.28	0.10	10.0	−0.72*	0.02	0.01	−0.01	0.00	1.00

Note: $n = 6300$, $^*p < 0.001$.

Probability for all organizations was 44% with a range from 2% to 99%. *Density* is by definition bound between 0 and 1. For our sample, *Density* ranged from 0.15 to 0.77 and is equal to 0.45 on average. *Diversity* is also by definition bound between 0 and 1, though, for practical purposes ranges from 0 to approximately 0.3. In the sample, *Diversity* ranges from 0.003 to 0.225 and is equal to 0.083 on average. *Size* was constrained between five and one hundred agents. Larger organizational sizes were not considered due to the computational time necessary to calculate probabilities for such structures.

Ordinary least squares regression was conducted to access the relative influence of density and diversity on probability as our likelihood parameter, β, is varied. Since our dependent variable is bound between 0 and 1, I perform a logistic transformation to *Probability* for estimation purposes. The linear form of this equation is presented in Eq. (18). (Note that in Eqs. (17) and (18), β represents an array of coefficient estimates, not our likelihood parameter.)

$$Probability = e^{\beta X}/1 - e^{\beta X} \tag{17}$$

$$\ln(Probability/1 - Probability) = \beta X \tag{18}$$

As independent variables (X), I include our measures of organizational design—Density, Diversity, Size—and our likelihood parameters—α and β.

In Table 3, I present the estimates to three specifications of our model. In Model 1, we find that the probability of discover increases as α is increased and β is decreased. These findings flow naturally from our model. As is shown in Eq. (4), as α is increased, the overall likelihood of discovery or transfer is increased regardless of the distance between knowledge positions. Conversely, as β is increased, the *lower* the likelihood of discovery or transfer as the distance between knowledge positions increases.

In terms of organizational design, we find not surprisingly that *Densit*y and *Size* are positively and significantly related to *Probability*. In other words, we find—all else being equal—the more communication links within the organization, the greater the likelihood of

Table 3. Organizational design and expected probabilities.

$d.v.$: Probability	1	2	3
Density	1.484***	1.474***	2.405***
	(0.166)	(0.165)	(0.220)
Density*β			0.245***
			(0.037)
Diversity	−0.234	3.772**	21.272***
	(0.386)	(1.509)	(1.927)
Diversity^2		−22.684***	−120.478***
		(8.256)	(10.497)
Diversity*β			−4.665***
			(0.326)
Diversity$^{2*}\beta$			26.280***
			(1.780)
Size	0.034***	0.034***	0.034***
	(0.000)	(0.000)	(0.000)
α	7.524***	7.526***	7.531***
	(0.065)	(0.064)	(0.063)
β	−0.386***	−0.386***	−0.087***
	(0.002)	(0.002)	(0.022)
intercept	−3.092***	−3.240***	−4.372***
	(0.088)	(0.103)	(0.133)
Observations	6300	6300	6300
Adjusted R^2	87.62%	87.64%	88.13%
F stat	8895.41***	7421.83***	5182.30***

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.
Standard errors in parentheses.

discovery. Similarly, we find the greater the number of agents, the greater the probability of discovery. The more agents in the firm, the more opportunities for someone to discover an innovation and to communicate that to others. The more links, the greater likelihood that someone else in the organization will communicate information regarding the innovation to another agent.

In Model 1, we do not find a significant linear relationship between *Diversity* and *Probability*. This is perhaps not surprising given that we expect there to be an inherent tradeoff with diversity. The greater the diversity of agents within the firm, the greater the likelihood of one of those agents discovering some innovation. Conversely, the greater the diversity of agents within the firm, the lower the likelihood that once discovered information regarding this innovation will be communicated to others within the organization. As a consequence, there is likely to be a non-linear relationship between *Diversity* and *Probability*. In Model 2 (Table 3), I present estimations from a model that includes *Diversity* squared. We find a significant, positive coefficient for *Diversity* and a significant, negative coefficient for

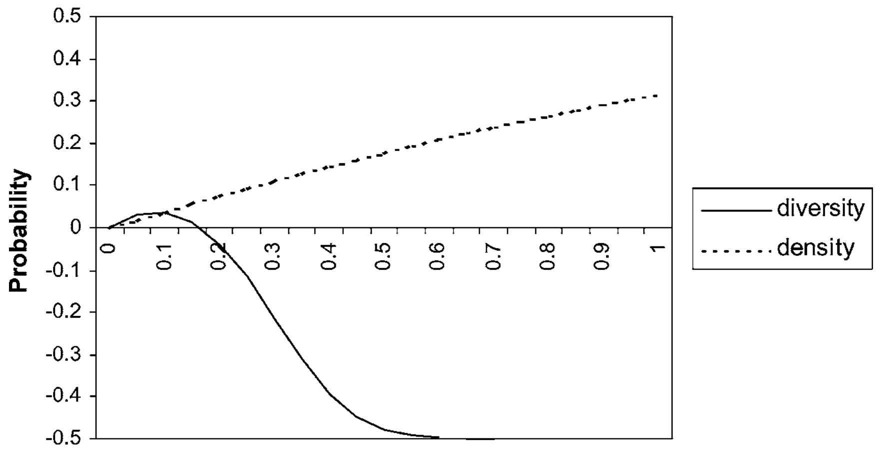


Figure 5. Value of diversity and density.

Diversity^2. Thus we find a concave relationship. As *Diversity* is increased, the likelihood of discovery at first increases only to eventually decrease.

Recall the interesting dynamic we observed as the parameter β is varied. As *Diversity* is increased, the likelihood of discovery at first increases only to eventually decrease (see figure 5).[2] In Model 3 (Table 3), I present the estimates from a specification including these interaction terms. Each of the interaction terms is significant and our overall model fit (adj. R^2) is improved. Mapping the impact of *Density* and *Diversity* on *Probability* as β is varied revealed an interesting dynamic. In figure 6, we find that in general increases in *Density* increase the likelihood of discovery. However, as the overall likelihood of transfer between agents is decreased, i.e. β is increased, the slope of this relationship approaches

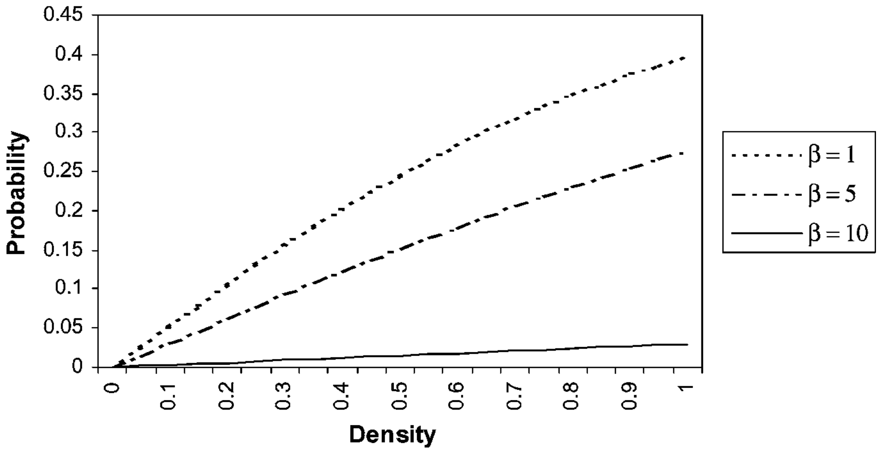


Figure 6. Value of density as β is varied.

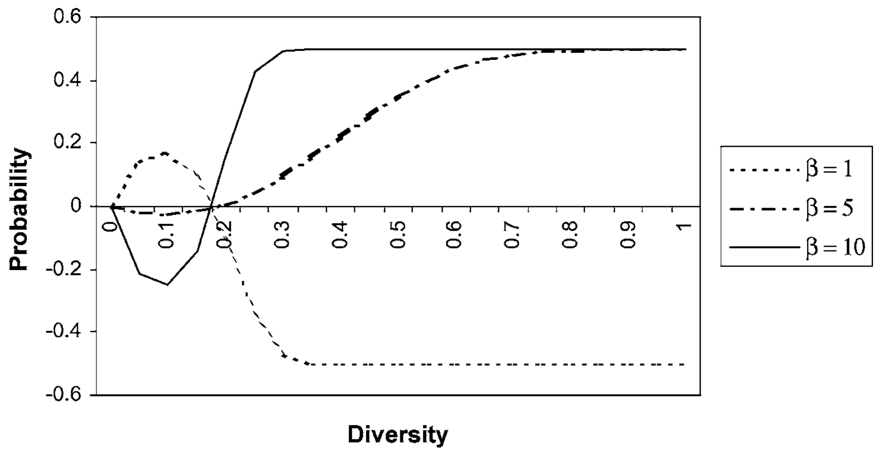


Figure 7. Value of diversity as β is varied.

zero. In other words, when the likelihood of transfer between agents is small, increasing communication links within the firm has negligible impact.

In figure 7, I present the impact that *Diversity* has on *Probability* as β is varied. For situations in which the likelihood of transfer is high ($\beta = 1$), we find the expected concave relationship. Interestingly, as β is increased (decreasing the likelihood of discovery and transfer), the relationship reverses. In other words, the value of diversity increases the lower the likelihood of discovery and transfer. Through experimentation, I find that at $\beta = 4.6$ one is indifferent to the level of diversity. For values of β greater than 4.6, there are growing incentives to increase diversity.

3.2. Identifying Optimal Structures

When expected profits are considered rather than the expected probability of adopting, it becomes difficult to determine which organizational features—diversity or density—matter most. For a given set of parameter assumptions, an optimal (or a set of optimal) organizational configuration exists. Unfortunately, we may not derive the optimal structure analytically for problems of even a small size N. To explore effective configurations in terms of expected profits, I calculated the returns to a variety of organizational configurations for a given set of parameters. In particular, I evaluated a tree, a circle, and a fully connected graph each with perfectly homogeneous and diverse agents. Out of the three, prototypical organizational structures with either diverse or homogeneous agents, the distributed circle fared best (see figure 8).

To explore potential superior configurations, I used a genetic algorithm (GA) to search for near-optimal organizational combinations. Search algorithms, such as the genetic algorithm, provide a convenient way to find near optimal solutions to highly non-linear fitness functions. To execute the algorithm, I represented the choice variable S (organization structure) as a binary array and the choice variable K (agent distribution) as an

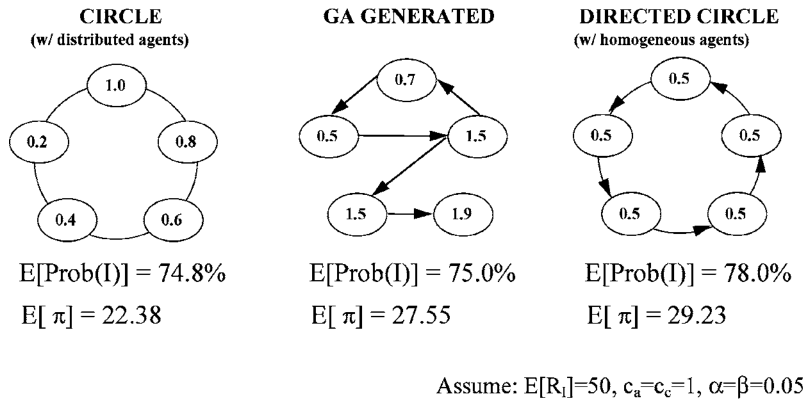


Figure 8. Testing for the best configuration for a given scenario.

array of real numbers. Single point crossover was performed on S while single element switches were performed on K. Mutation involved switching bits in S and generating new values in K. To reduce computation time, organizations were restricted to five agents.

Using a population of twenty organizations and iterating twelve hundred times led to the configuration shown in figure 8. The genetic algorithm was able to find a configuration that was nearly 25% better than my previous best calculation—the distributed circle. In addition, the GA generated configuration had a slightly higher expected probability of adopting innovations while using half the number of links. Based on this result, I calculated the expect profits for a directed, homogeneous circle and generated still higher payoffs. Interestingly, this structure generated an adoption probability only slightly lower than the fully connected graph.

4. Discussion

The primary insight gained from experimentation concerns the relationship between diversity and density as the general likelihood of discovery varies. To summarize, the greater the probability that organizational agents discover innovations from outside the organization, the greater being well connected influences the expected probability of adopting innovations should they arise *and* the lesser the distribution of agents matters. Furthermore, the lesser the probability that organizational agents discover innovations from outside the organization, the greater having diverse organizational members influences the expected probability of adopting innovations should they arise *and* the lesser the connectedness of the organization matters.

In situations of high discovery probability, regardless of location in knowledge space, agents are likely to discover innovations. In these situations, being able to transfer information from those who discover the innovation to others, confers a much higher likelihood of adoption overall. Conversely, in situations of a low probability of discovery, agents are highly unlikely to discover innovations. Therefore, the likelihood that an agent will discover and transfer information is extremely low. In such situations, the greatest likelihood that an organization will adopt will be if agents discover the innovation themselves. Having diverse agents aids in this situation since it increases the likelihood that some agent in the organization will discover the innovation independently.

In many ways, these results are in line with organization theorist's observations about structure, environment, and innovativeness. One may define a state of the world in which there exists a high likelihood of discovering innovations as a "certain" environment. Conversely, a world in which discovery is low may be characterized as "uncertain". Highly diversified yet marginally connected organizations correspond to "organic" structures, while more homogeneous, tightly connected organizations may be viewed as "mechanistic". As proposed by contingency theorists and echoed by some diffusion theorists, the model presented here suggests that organic structures are preferable in uncertain environments while mechanistic structures are desired in more certain environments.

The results are also complementary to contagion theories of diffusion (Rogers, 1995). Early in diffusion processes when awareness of innovations is low, we would expect there to be a low probability of any agent discovering an innovation. Consequently, we would expect organizations that have diverse organizational members to be early adopters regardless of the number of organizational communication linkages. As contagion effects take hold and greater numbers of people become aware of the innovation, the probability of any agent discovering an innovation rises. As the likelihood of discovery rises, we would expect organizations that are internally well connected to be likely to adopt the innovation regardless of the diversity of their members. To state this another way, early on in diffusion processes being able to explore large knowledge spaces is critical, i.e., exploration is important. Later in the diffusion process the ability to transfer knowledge internally is critical, i.e., exploitation is critical.

4.1. Limitations

While insightful, the model presented in this paper has a number of limitations. In the model, agents do not engage in a specific operational task such as classification (e.g. Carley, 1998). For the sake of parsimony, the model focuses purely on the discovery of rent-producing resources or capabilities (i.e. innovations). As a consequence, we cannot explore the short-run operational implications of various organizational structures. The addition of a classification task among the agents would provide an interesting comparison to the results presented in the paper.

In addition, the model does not explicitly address issues of organizational adaptation and change. In this paper, I assess the likelihood of discovering innovations for particular organizational structures. I do not consider how these structures may be updated over time. Thus, a whole host of questions that have been of interest to computational organizational theorist cannot be addressed in this model. The model does provide a framework, however, to begin to explore more complex (and more realistic) environments. The genetic algorithm provides a useful descriptive model of how organizations may update their structure as they receive feedback concerning the profitability of various organizational configurations. Using the genetic algorithm, we may create an artificial world to explore the dynamics of organizational change. We may observe the conditions under which populations of organizations converge to similar configurations or whether punctuated equilibrium may arise. More complex models may be created where firms not only race to first recognize and acquire valuable resources and capabilities but can shape which resources and capabilities are valuable by their very actions.

5. Conclusion

This paper provides a foundation upon which to understand how competitive advantage is built and sustained. At the root of sustained competitive advantage is a superior ability to recognize and adopt valuable new resources and capabilities that allow a firm to achieve favorable market strategies. This dynamic capability depends on the firm's prior knowledge accumulated over the history of the firm and embedded in organizational routines and structures. The model presented in this paper is provides a template to explore the relationship between organizational structure and dynamic capability.

In particular, this paper explores the possibility of firms to structure their organization so as to increase the likelihood that they will recognize and value rent-producing resources and capabilities. It provides a model to begin to analyze the tradeoffs between exploration and exploitation inherent in integration. Support is provided for the proposition that integration, both externally and internally, is an important source of dynamic capability. The model provides greater insight into the tradeoffs between these two forms of integration and suggests when one form may be preferred over another. In particular, evidence is provided that in uncertain environments, the ability to explore possible alternatives is critical while in more certain environments, the ability to transfer information internally is paramount.

This paper represents an important step towards a more robust understanding of how organizational structure relates to dynamic capability. This paper provides an important link between the strategy literature on dynamic capabilities and the organizational design and learning literatures. To the extent that the ability to achieve advantageous positions in competitive markets is determined by the acquisition of valuable resources and capabilities in imperfect factor markets, there is much to be gained from incorporating models of organizational information processing into our understanding of dynamic capability.

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