Choice Interactions and Business Strategy

Prof. Pankaj Ghemawat
Morgan Hall 227
Harvard Business School
Boston, MA 02163
617-495-6270
pghemawat@hbs.edu

Prof. Daniel Levinthal
2035 Steinberg-Dietrich Hall
The Wharton School
University of Pennsylvania 19104
215-898-6826
Levinthal@wharton.upenn.edu

February 2006

We wish to thank seminar participants at Harvard Business School, INSEAD, the University of Illinois at Urbana-Champaign and the University of Southern California as well as the Department Editor who processed this paper, Rebecca Henderson, and three anonymous reviewers for their thoughtful comments on earlier drafts.

Choice Interactions and Business Strategy

Abstract:

Choice settings are strategic to the extent that they entail cross-sectional or intertemporal linkages. These same factors may impose daunting demands on decision makers. We develop a graph-theoretic generalization of the NK model of Kaufman (1993) in order to model the way in which policy choices may be more or less strategic. We use this structure to examine, through simulation, how fully articulated a strategy or set of policy choices must be to achieve a high level of performance, and how feasible it is to offset past strategic mistakes through tactical adjustments (instead of alignment). Our analysis highlights the role of asymmetry in the interaction of strategic choices and in particular the degree to which choices vary in terms of being influential, dependent, or autonomous from other choices.

Choice Interactions and Business Strategy

1. Introduction

The interactions among choices are essential to firm strategy. In the absence of cross-functional interactions, for example, choices could be made from a functional perspective, shrinking the scope for strategy to have distinctive content as a field, beyond that offered by individual functions. And without intertemporal interactions, choices could be made myopically, without requiring any sort of deep look into the future (a point first stressed by Arrow 1964).

Strategists have responded by exploring the interactions among firms' choices both synchronically and diachronically, to use the conventional historical categories. Synchronically, there has been renewed interest in the multidimensionality of and complex interactions among a firm's policy choices at a point in time (e.g., Porter 1996; Levinthal 1997; Rivkin 2000). And diachronically, a number of authors have explored how earlier choices may influence later ones (e.g., Ghemawat 1991; Teece, Pisano, and Shuen 1997). But while these extensions are essential, dealing with them does present some difficulties for strategy-making. In particular, both synchronic and diachronic interactions induce complexity in the sense of introducing interdependency among choices (Simon 1962). This property, in turn, makes it hard to imagine boundedly-rational actors prespecifying all relevant policy choices, let alone rules governing their optimal evolution.

For that reason, we focus on a different behavioral mechanism in which boundedly rational agents—companies that are profit-seeking but not profit-maximizing—first precommit to particular policy choices for a subset of the possible dimensions of choice ("strategy setting") and then follow up with (local) search and adaptation ("tactical alignment") over the fitness landscape defined by the payoffs associated with different combinations of policy choices (Gavetti and Levinthal 2000; Siggelkow 2002a).

The principal question of interest to us here is how well this mechanism should be expected to work in dealing with multiple, interacting dimensions of choice. There are two obvious types of contingencies to be explored in this context: those in which initial strategic precommitments align with the choices that turn out to be optimal *ex post* and those in which the two are misaligned. We use agent-based simulations to analyze both types of contingencies. The analysis of the alignment contingency focuses synchronically on the completeness with which strategies must correctly be prespecified to achieve satisfactory performance and, in particular, the implications of correctly prespecifying policy choices that are more strategic versus merely a greater number of policy choices. The analysis of the misalignment contingency looks diachronically at the dark side of precommitment: the performance implications of irreversible mistakes in past choices.

Our results are grounded in a structure for representing choice interactions that permits systematic exploration of the performance impact of interaction-related attributes of choices—particularly influence versus dependence and centrality versus independence—as opposed to choices' standalone attributes. This structure and its links to prior work in strategy and other fields are discussed next, before the model employed in this paper is fully presented and analyzed.

2. From Activity Systems to Adjacency Matrixes

The strategy field has long emphasized the importance of understanding the interactions or interdependence among firms' policy choices. Early work such as Andrews (1971) took a primarily synchronic perspective by focusing on cross-functional interactions; diachronically, this work did acknowledge the existence of resources or, more broadly, strengths and weaknesses, with long-lasting effects but simplified matters by treating them as fixed for purposes of strategic planning. Porter (1996) provided a much more articulated sense of synchronic choice interactions with "activity systems" that highlighted the linkages among rather detailed operating choices as well as their interactions with—and the interdependence among—a small number of higher-order choices about how a firm positions itself relative to the competition: see **Figure 1** for an example, based on the case of Southwest Airlines. Attention to diachronic interactions is more recent but has already afforded some insights into how earlier choices may affect later ones (e.g., Ghemawat 1991 on irreversibility and commitment, and Teece, Pisano, and Shuen 1997 on path-dependence).

Grappling with interactions among choices poses challenges for decision makers because of what Bellman (1957), one of the progenitors of dynamic programming, described as "the curse of dimensionality." The difficulties are twofold. Even within a purely synchronic or cross-sectional frame, rich interactions among a large number of choices imply, given the combinatorial possibilities, the nonexistence of a general, step-by-step algorithm that can locate the best set of choices in a "reasonable" period of time (i.e., a polynomial function of the number of variables) (Lewis 1985; Rivkin 1997). And from an diachronic perspective, such systems generally do not lend themselves to "pushing forward" in time from multi-dimensional histories to identify an optimal path on the basis of a lower-dimension set of choice variables, even if those are the only variables of direct interest (Sussman 1975).

How can firms cope with such complexity? Here, the literature on strategy-making is less explicit but often seems to assume that strategies are specified *ex ante*, on the basis of *a priori* theorizing. And here, we break with orthodoxy and, following Simon's (1955) arguments regarding bounded rationality, treat complexity as an inexpungible constraint. The boundedly-rational behavioral mechanism that we posit—a firm partially precommitting to its choices, and then engaging in a process of local search and adaptation—will be specified more precisely in the next section. While bounded rationality is often viewed from the lens of the degree of actor's cognitive capabilities, whether this constraint binds, and its effects if it does, depend on the decision contexts in which actors find themselves (Ethiraj and Levinthal 2005). Different structures of interaction pose different degrees of challenge for boundedly rational strategy-making.

One way forward is to recognize, as emphasized in Simon's early work on the architecture of complex systems as well as more recent writings on modularity (Baldwin and Clark 2000), that even in complex design problems, not all elements of the design (i.e., strategy) problem affect one another, nor are the interactions that do exist likely to be symmetric or randomly distributed. The possibility that there may be some underlying structure to the interactions of strategy choices provides some hope that the identification of a subset of critical strategy choices may be sufficient to orient the firm towards an effective position on the competitive landscape. What constitutes a "critical" choice in this context is a function of the interaction structure among the choices. If, as Simon (1962) suggests, design problems tend to have some inherent hierarchy, then it might be reasonable to assume that choices higher up in the hierarchy of policy choices, that is choices that influence the appropriate resolution of other choices, would be particularly important to specify correctly.

More broadly, the articulation of the underlying structure of such choices might prove a useful substrate to theorizing about strategy development. Siggelkow's (2002a) work on the historical development of the activity system(s) for Vanguard's mutual funds can be used to illustrate the dependence of effective strategy-making on the underlying structure of choices. One developmental process considered by Siggelkow is "patch-to-patch." The image is that one sub-system of a firm's strategy, such as its product positioning, becomes fully characterized and then, in a sequential manner, other "sub-systems" are characterized. An alternate process is what Siggelkow terms from "thick-to-thin." In this dynamic, broad, higher-order policies are first identified and then subsequently lower-order, more refined policies are specified. Building on Simon (1962), we suggest that the former process would be effective to the extent that the interdependencies among choices are nearly decomposable. Only in such a setting can one intelligently specify the elements of one subsystem in isolation. The second process, "thick-to-thin" would seem to be effective to the extent that there is some inherent hierarchy in the set of choices, that the identification of a few higher-order choices can broadly situate the firm in the competitive landscape and effectively seed the subsequent process of local search.

A general structure within which to explore the impact of varying patterns of interaction is suggested by the observation that the activity system in **Figure 1** bears some resemblance to a mathematical graph. A mathematical graph can be summarized in terms of its adjacency matrix, which specifies how different choices—the vertices in the graph—are linked by the lines in the graph (see **Figure 2** for examples). In such a matrix, choice variable i's effect on other variables is represented by the patterns of 0's and 1's in column i, with a value of 1 indicating that the payoff associated with the variable in the row being considered is dependent on variable i, and a value of 0 denoting independence. A choice is influential to the extent that the column under that policy is populated with 1's, indicating that the value of other policies depends on this choice. Conversely, a policy is dependent upon other choices to the extent that the row corresponding to that policy is populated with 1's in the adjacency matrix.[1] A policy is relatively autonomous to the extent that neither the column nor row associated with this policy is populated with 1's. Also, note that the principal diagonal of an adjacency matrix always consists of 1's.

However, while there is a resemblance between activity systems of the sort depicted in **Figure 1** and adjacency matrices populated with 0's and 1's, it stops well short of isomorphism. There are three principal differences that are worth emphasizing. First, our adjacency matrix approach does not prespecify a distinction between higher-order and lower-order strategic choices (the darker versus lighter circles in **Figure 1**): the focus here is on identifying the choices that are strategic in terms of their interactions with other choices instead of presorting them independently of that structure. Second, the adjacency matrix approach allows for a distinction that the activity system approach, as conventionally articulated, does not: it unbundles linkages by directionality (influence versus dependence). Third, the activity systems approach tends to assume that all strategic choices are freely variable in each period whereas the adjacency matrix approach accommodates more interesting diachronicity by allowing for temporal precedence. The last two enhancements associated are worth discussing in more detail.

The enhancement of allowing for directionality in linkages is necessary only if adjacency matrixes are asymmetric around the main diagonal, i.e., if influence/dependence is not always reciprocal. Clearly, temporal precedence can engender such asymmetries, a possibility that we address below. What is less obvious is whether, within a purely synchronic frame, choice "A" can affect the payoff consequences of a second policy choice "B" without symmetrical interdependence being present. Guidance in this regard is offered by the literature on product design, which has developed design structure matrixes that are formally equivalent to the adjacency matrixes considered here. For instance, MacCormack, Rusnak, and

[1] In addition to such direct effects, variables may, of course, be indirectly related through other variables.

Baldwin (2004) offer a clear illustration of an asymmetric relationship in the context of computer programming.[2] More generally, analyses of interactions in actual technical systems reveal strong asymmetries, such as Baldwin and Clark's (2000) analyses of computer systems or Sharman and Yassine's (2004) work on gas turbines.[3]

We therefore allow for directionality in linkages by distinguishing between influence and dependence as well as considering the overall intensity of a choice's linkages to other choices. It is worth adding that these are all well-established notions in the design literature. That literature typically uses the term "visibility" rather than influence, where an element is "visible" to another if changes in its value affect the performance of the other element (Sharman and Yassine 2004). However, visibility is defined in exactly the same manner in which we define influence: the number of 1's in the column associated with that policy choice in the design matrix. Furthermore, the term "dependence" is used in this literature exactly as employed here: the number of 1's in the row associated with that policy choice in the design matrix. The literature also notes that systems may vary in their level of overall connectivity or interdependence.

The final enhancement associated with the adjacency matrix approach, the ability to allow for the sequencing of choices, is also evident in the literature on design structure matrixes, which sometimes uses them to map process flows. For example, choices that must be made in a strictly linear sequence can be represented as a diagonal of 1s just below the main diagonal. In the current analysis, we look at diachronic interactions within the simplified context of a two-stage choice process, with a focus on the consequences of correct versus incorrect specifications in stage one given local search and adaptation in stage two.

---

[2] Their example concerns computer programming and function calls, i.e., instructions that require specific tasks to be executed by programs. When the function that is called is not contained within the source program (or sub-routine), "this creates a dependency between the two sources files [programs] in a *specific* (italics in the original) direction. For example, if Sourcefile1 calls FunctionA, which is located in Sourcefile2, we note that Sourcefile1 depends on Sourcefile2. . . . Note that this dependency does not imply that Sourcefile2 depends upon Sourcefile1." (MacCormack, Rusnak, and Baldwin 2004: 9).

[3] Rivkin and Siggelkow (forthcoming) make a similar argument for the presence of asymmetric off-diagonal elements of an adjacency matrix in their examination of the structure of interaction among a firm's policy choices.

Despite this last simplification, the structure of choices set up and analyzed in this paper admits a wide range of interactions. As Sharman and Yassine (2004) note, we may observe a number of qualitatively different patterns in a matrix structure depending on the degree to which visibility (influence) is symmetric and the degree of connectivity (interdependence) in the system. **Figures 2a-2d** span a wide range of patterns of interactions. **Figure 2a** is a relatively hierarchical matrix in that elements (policies) that are very influential tend not to depend on other elements, whereas **Figure 2b** is rather more symmetric in the sense that influential elements tend to be highly dependent as well. Systems may also vary in the degree to which elements are interdependent. **Figures 2c** and **2d** display systems that are relatively hierarchical and relatively symmetric respectively, but with much lower levels of interdependence than in **Figures 2a** and **2b**. This paper focuses on the implications of these attributes of choice interactions for the possibility and effectiveness of strategy-making.

3. Modeling Interactions

The challenge of modeling interdependent choices has recently received considerable attention in the economics and management literatures. One approach has been to focus on a very special choice structure, involving supermodularity, in which choices along any two dimensions are pair wise complementary for all values of the choice variables involved, and for all values of other choice variables. Topkis (1978 and 1995) and Milgrom and Roberts (1990 and 1995) have used the resulting lattice models to show that these are the weakest conditions under which it is possible to obtain monotone comparative static predictions linking shifts in optimal choices concerning sets of variables to changes in underlying parameters. How weak these conditions are in absolute terms is another matter: tradeoffs or substitution effects are ruled out, as are reversals between substitution and complementarity as the values of relevant variables change and, consequently, limitations are placed on the number of “best ways to compete” (local peaks on the fitness landscape, as elaborated below). If one believes, as some strategists (e.g., Porter 1996) do, that the interplay between complementarities *and* trade-offs across multiple activities is critical to the possibility of "many best ways to compete," then allowing only global complementarities seems very constricting.

The other response to the problem of multiple, linked choices that has commanded attention recently has been to build on the NK-simulation approach pioneered by Kauffman (1993) in evolutionary biology (cf., Levinthal 1997 and Rivkin 2000). Kauffman, drawing on Wright's (1931) notion of a fitness landscape, developed this framework to explore the emergence of order among biological organisms. The model has two basic parameters, N, the total number of policy choices, and K (< N), the number of policy choices that each choice depends upon. More specifically, each of the choices is assumed to be binary, and choice-by-choice contributions to fitness levels are drawn randomly from a uniform distribution over [0,1] for each of the 2^{K+1} distinct payoff-relevant combinations of which a choice can be part. Total fitness is just the average of the fitness contribution of each of the N individual fitness levels. Note that with K equal to its minimum value of 0, the fitness landscape is smooth and single-peaked: changes in the setting of one choice variable do not affect the fitness contributions of the remaining N-1 choice variables. At the other extreme, with K equal to N-1, a change in a single attribute of the organization changes the fitness contribution of all its attributes, resulting in many local peaks rather than just one, with each peak associated with a set of policy choices that have some internal consistency. No local peak can be improved on by perturbing a single policy choice, but local peaks may vary considerably in their associated fitness levels.

The choice structure underlying the NK simulation approach generalizes Milgrom and Roberts' lattice-theoretic approach based on "complementarities" in two key respects. First, it avoids imposing a specific structure on the linkages among choices. Second, it allows the richness of such linkages to vary across situations (through the K parameter). It embodies a number of other attractions as well, most of which we will discuss and retain below. But for our present purposes, it also has one glaring defect: all choices are assumed to be equally important. This rules out, for example, asymmetries of the sort evident in the distinction between light and dark circles in **Figure 1**. To remedy that defect, we need more degrees of freedom than are afforded by a single interactivity parameter, K. This is precisely what adjacency matrixes of the sort discussed above afford: the ability to vary in the degree to which choices influence or are influenced by others.

For concreteness, reconsider the two examples cited earlier. Vanguard has been characterized as having been founded on the basis of a highly distinctive choice of organizational structure from which other choices naturally flowed (Siggelkow, 2002a). The Vanguard Group was incorporated as a mutual holding company in which the shareholders of the underlying funds would own the managing fund complex.[4] As a true mutual, administrative services shifted from being a source of profits for the fund manager to being a "cost center" shared by the underlying mutual funds and, correspondingly, provided a focus on cost reduction not shared by other fund complexes. Resulting choices, such as the focus on index funds, internalizing much of the asset management function, and the shift to direct distribution of funds to shareholders, as opposed to the then conventional format of broker-dealers, followed quite naturally from this prior choice of organizational form.

Thus, the set of interrelationships among policy choices in the case of Vanguard appears to have a hierarchical quality. The most stylized representation of this sense of hierarchy would be to consider the adjacency matrix corresponding to the Vanguard characterization as containing 1's in one column (corresponding to the choice of organizing as a "true" mutual) as well as in the principal diagonal, with 0's elsewhere—in graph-theoretic terms, a star. A star graph is an extreme example of the much more general class of hierarchical choice structures. In graph-theoretic terms, hierarchies are best thought of as directed (or at least rooted) trees, with interdependencies (i.e., the 1's) populating one side of the principal diagonal. **Figure 2a** actually depicts a pure hierarchical form with 1's as all the entries to the left of the principal diagonal. Choice 1 is hierarchically the most important, choice 2 the second most important, and so on; such a structure lets us take a finer-grained look at the effects of variations in the degree of hierarchical importance than a star structure would permit.

---

[4] The term mutual fund refers to the joint holding of investment assets. However, with the exception of Vanguard, all "mutual funds" are structured such that shareholders in the fund have no ownership of the entity that manages and administrates the investment assets.

The Southwest activity system in **Figure 1**, in contrast, does not lend itself to representation in hierarchical terms. Instead, the policy choices captured by the circles vary in their degree of centrality, i.e., the number of other choices on which they are mutually dependent. Thus, "point to point routes," with five links, is more central to Southwest's strategy than, say, the lack of seat assignments with one such link. In addition, the purely cross-sectional nature of the representation suggests that this notion of centrality is responsive to the potential inferential problem that all we might be able to observe are the linkages between choices, not the direction of influence, i.e., that in observational terms, we might have to work with undirected graphs—or in adjacency matrix terms, with matrices that are symmetric around the principal diagonal. The particular form of centrality depicted in **Figure 2b** embodies a structure and a labeling scheme that has 1's as all the entries to the left of the inferior diagonal (but distributed symmetrically to the left and the right of the principal diagonal). Thus, choice 1, with links to 9 other choices, is the most central, choice 2 the second most central, and so on.

To explore systematically a range of possible adjacency matrices, we specify the following stochastic process for generating them. For each policy choice, we specify a probability p_i^H that policy i influences other policy choices and a probability p_i^C that the payoff to this policy is in turn dependent on other policies. Thus, the likelihood of a linkage such that choice i influences policy choice j is $p_i^H\, p_j^C$. Or, to reparametrize these variables, p_i^H and p_i^C, in a useful way, let $r_i = p_i^H / (p_i^H + p_i^C)$ represent the relative tendency towards influence as opposed to dependency, and let $p_i = (p_i^H + p_i^C)$ represent the likelihood of some form of interdependence as opposed to independence.[5] Thus, by varying r_i from zero to one we specify the relative degree to which a policy is dependent or influential and by varying p_i from zero to one we vary the policy's degree of interdependence.

Specifically, we examine two sorts of structures of interactions among choices. One structure examines the effect of heterogeneity among choices with respect to the hierarchy of interactions, while the other examines the heterogeneity among choices with respect to the centrality of interactions. To

---

[5] Using this parameterization, $p_i^H = p_i r_i$ and $p_i^C = p_i\,(1 - r_i)$.

examine the first sort of structure, we set p_i equal to a constant value for all choices (with 0.5 being the base case for this fixed value) and vary r_i from 1 for the first policy to 1/N for the Nth policy in increments of 1/N in order to explore structures in which policy choices vary in the degree to which they are influential or dependent. Thus, the first decision would have a value of r of 1 and a value of p at a fixed level p_0 (again, with $p_0 = 0.5$ in the base-case), the second policy a value of r of (1 – 1/N) and a value of p of p_0 and so on. Similarly, variation in centrality is examined by setting r to a fixed value of r_0 (again, with $r_0 = 0.5$ in the base-case) and varying the value of p from 1 to 1/N in increments of 1/N. Therefore, when examining heterogeneity in centrality, the first policy has a value of p of 1 and a value of r of r_0 (again, with $r_0 = 0.5$ in the base-case), the second policy having a value of p of (1 – 1/N) and a value of r of r_0 and so on.[6]

For all interaction structures studied, an organization's policy choices are represented by a vector of length N where each element of the vector can take on a value of 0 or 1 (not to be confused with the 0's and 1's that are used to denote the absence or presence of linkages between every pair of policy elements). The overall fitness landscape will then consist of 2^N possible policy choices, with the overall behavior of the organization characterized by a vector $\{x_1, x_2, \ldots, x_N\}$, where each x_i takes on the value of 0 or 1.[7] If the contribution of a given element, x_i, of the policy vector to the overall payoff is influenced by K_i other elements—in ways that vary across the three structures we will analyze—then it can be represented as $f(x_i| x_{i1}, x_{i2}, \ldots, x_{iK_i})$. Therefore, each element's payoff contribution can take on 2^{K_i+1} different values, depending on the value of the attribute itself (either 0 or 1) and the value of the K_i other elements by which it is influenced (with each of these K_i values also taking on a value of 0 or 1). Specifically, we follow prior researchers and assign a random number drawn from the uniform

[6] To provide some comparison with the more familiar analysis of fitness landscapes with a fixed K value for all policy values, the baseline parameter settings here generate adjacency matrices with, on average, 14 non-diagonal 1's which implies, given a value of N of 15, a realized average K value of approximately 1. There is a slight difference between the hierarchical and centrality structure though the magnitude of this difference is quite small with the centrality structure having, on average 1.2 more non-diagonal values out of the 225 entries in the 15x15 adjacency matrix.

distribution from 0 to 1 to each possible $f(x_i| x_{i1}, x_{i2}, . . . , x_{K_i})$ combination, with the overall fitness value then being defined as $\sum_{i=1 \text{ to } N} f(x_i| x_{i1}, x_{i2}, . . . , x_{iK_i}) / N$.

A number of additional assumptions, based on prior applications, that are built into this specification should also be mentioned. First of all, there is the emphasis on choice under uncertainty. In addition to its arguable descriptive realism, initial uncertainty helps explain why an organization launched over a fitness landscape may not instantly alight on the globally optimal policy vector. Second, there is the assumption that randomness takes the form of a uniform distribution. While it could be argued that this distribution is too diffuse, we retain this assumption to provide at least some basis for numerical comparability with prior work; furthermore, prior work by Weinberger (1991) and others suggests that the structure of the fitness landscape is not sensitive to the probability distribution employed. Third, there is the equal weighting of different choices in terms of their direct contribution (potential) to overall fitness. Solow *et al.* (1999) explore the implications of differentially weighting the contribution of different policy variables to overall performance.[8] While asymmetries in weights are clearly important, our focus here is on asymmetries in the structure of interactions and their implications for effective strategy formulation. Finally, note that while the analysis highlights the effects of linkages among the organization's policy choices, it does not address linkages across firms. In particular, one could imagine spatial competition (or cooperation) among firms so that the fact that one or more firms occupy a particular point on the policy landscape changes the payoff to other firms' occupying that region (see, for example, Lenox *et al*. 2005). Clearly, such effects exist and are important. But, for simplicity, we do not explore them in the present analysis.

We also assume that N equals 15—a level of multidimensionality that, based on a standard result in graph theory, is sufficient to generate more than 10^{19} distinct graphs. The results that we report are

---

[7] The model can be extended to an arbitrary finite number of possible values of an attribute, but the qualitative properties of the model are robust to such a generalization (Kauffman 1989).
[8] The focus of their work is to demonstrate that sufficiently extreme weighting differences, in particular weighting the contribution of one policy by 1-ε and the other N-1 variables by ε for sufficiently small values of ε, can allow a

averaged over 10,000 landscapes. The repetition is meant to allow for the averaging out of two kinds of randomness. The first reflects the range of possible adjacency matrices that may result for a given set of values of p and r; the second results from the seeding of a given performance landscape. To address the former source of randomness, we generate 100 adjacency matrices for each vector of p and r values. Each of these 100 landscapes will have an independently drawn adjacency matrix, although based on the same p and r values. In addition, given the realized adjacency matrix, the landscapes will have a distinct seeding of fitness values. To address the latter sort of randomness, we generate 100 distinct fitness landscapes for each of these 100 adjacency matrices. In analyzing our results, we normalize fitness levels, in a manner now standard in analyses of such structures (cf., Rivkin 2000; Rivkin and Siggelkow 2003), to control for the fact that the magnitude of the global peak will vary from landscape to landscape, even if the landscapes share the same structural properties. As a result, the highest possible performance is specific to a particular fitness landscape and therefore, what is "good" performance must be evaluated relative to the value of the global peak in that particular landscape. Thus, the fitness values provided in our results are the raw fitness value divided by the fitness value at the global peak for the particular fitness landscape in which the firm is operating. These normalized fitness levels, averaged over the 10,000 runs, are what are actually reported in the next section.

4. Simulation Results

We explore the emergence of strategic positions from two perspectives, both of which involve strategic choices followed by local search over what might be described as tactical choices. We first look at the possibility, or demands, of *a priori* specification of strategies: can higher-order or strategic guidance along a few dimensions followed by tactical adjustment and alignment of the remaining dimensions through local search be expected to lead to high levels of performance? Second, we consider diachronic or temporal linkages in conjunction with synchronic interactions. In particular, we consider the

---

process of local search to reach the global optimum even under conditions of high interaction (K) across policy impact of legacy misspecification of policy variables that are strategic in the sense of being irreversible: what are the residual costs of different types of initial misspecified choices, after local search and tactical adjustment aimed at mitigating these "mistakes" or unfortunate legacies from a prior competitive setting?

Strategic Guidance and Tactical Alignment

How might a complex policy system such as the cross-sectional one depicted in **Figure 1** for Southwest Airlines arise? Broadly speaking, there are two possibilities. One is through *ex ante* design of a coherent and fully articulated activity system. Another possibility is via a process of search and adjustment on the fitness landscape defined by the payoff associated with different vectors of policy choices. In particular, a process of local search will eventually identify an internally coherent set of policy choices; that is, a set of choices from which any incremental one-policy-at-a-time change would be dysfunctional, or what has been called a local peak in the fitness landscape (Kauffman 1993). However, local peaks come without warranties as to their global or absolute desirability, so there is no assurance that local search processes will, on their own, lead to satisfactory performance.

The actual evolution of successful strategies probably involves elements of both *ex ante* design and *ex post* adjustment. Full articulation *a priori* of a strategic position with dimensionality as high as in **Figure 1** seems daunting; at the same time, it seems unlikely to be purely emergent. A plausible picture of managerial processes seems to be that while there is some top-down prespecification of both some broad principles and some particular policy choices, these represent starting points of processes aimed at improving firms' positions over time (Gavetti and Levinthal 2000; Siggelkow, 2002a). This representation also has the attractive feature of embodying elements of both the conscious choice of strategies, in the spirit of the "content" style of strategy research, and of the emergence of strategic positions that is central to "process" discussions of strategy formulation (Mintzberg 1978; Burgelman 1994).

---

choices.

Our use of this representation is motivated by the idea that the effectiveness of strategic planning may be inversely related to the dimensionality required of a strategy to ensure the achievement of a reasonably consistent set of policies. If strategy must be defined at a very detailed operational level to achieve consistency (e.g., if it must spell out the choices corresponding to all the circles in **Figure 1**), then the requirements for strategic planning escalate dramatically. In contrast, if a few higher-level choices make subsequent lower-level choices self-evident (e.g., if it suffices to spell out the choices corresponding to just the dark circles in **Figure 1**, followed by a process of local search), then the requirements for strategic planning remain relatively modest.

Tables 1 and **2** explore this issue for the hierarchical and centrality structures respectively, in the following manner. A certain number of policy choices ("degree of match"), selected in decreasing order of "strategic" importance (with reference to the hierarchical and centrality structures), are set to equal their value at the global optimum, and the initial values of the remaining policy choices are specified at random. In this sense, the analysis provides an optimistic account of the possible power of *a priori* strategy setting in that the explicit strategy choices are assumed to be correct, but the question remains as to how deep and fine-grained must strategy-making be for such *a priori* choices to ultimately result in desirable overall policy configurations. These remaining policies are then modified by a process of local search. Local search (March and Simon 1958; Cyert and March 1963) involves the comparison of an existing policy choice with adjacent, or neighboring choices. This process is operationalized here as involving the comparison of the current policy vector with all the other policy vectors that differ from the current vector in terms of just one choice element. If a superior alternative is identified in the immediate neighborhood of the existing policy array, it is adopted.[9] In subsequent periods, more local search follows until no further replacement that immediately enhances fitness values can be found. This dynamic leads, inexorably, to local peaks in the fitness landscape (Levinthal 1997). Thus, the choice variables that are

[9] More precisely, local alternatives are sampled at random until a superior (relative to the current policy) alternative is identified or the entire set of neighboring points is exhausted. An alternative specification would be to impose a

correctly preset influence the initial seeding of the organization in the fitness landscape. From this starting point, the organization then identifies a local peak within whose "basin of attraction" it has fallen.

With a preset degree of match of 1, only the first, most strategic, variable is set equal to the global optimum. As more variables are matched with their settings at the global optimum, fitness rises steadily according to both tables**.** Not surprisingly, presetting more policy choices correctly monotonically enhances the expected performance of the policy configuration that the firm ultimately identifies. However, it is striking how extensive such a specification must be in order to reliably obtain the global optimum. As a further test of the importance of identifying relatively strategic policies for strategy-making, we also consider a random baseline in which the matrix of interactions is the same (hierarchical or centrality) but the policies that are correctly pre-specified are randomly chosen. We observe two sorts of resulting performance differences in the two tables. Specifying more strategic, rather than random, policy choices leads to a superior initial value.[10] This superior initial "seeding" of the organization in the performance landscape, in turn, leads the subsequent process of tactical adjustment of policy choices to result in the identification of a superior local peak as revealed by the comparison in final fitness value in the two regimes. The gap between performance under such a random choice of polices to prespecify correctly and performance that results from the "ordered" specification of correct policy choices indicates the power of presetting more strategic variables. In contrast, the gap between the realized fitness level and the (normalized) value of 1, indicates the loss from not fully articulating the optimal policy array. This analysis implies, most broadly, that *a priori* strategy-making matters. The more policies that can be specified correctly *a priori*, the higher the level of fitness the organization is able to obtain subsequent to its process of local search. Further, specifying more strategic policies correctly has a statistically significant effect on the resulting performance. However, a high level of specificity is necessary to obtain

---

"greedy" local search in which all local alternatives are evaluated and the best among these, if it is superior to the status quo, is adopted.

[10] Statistical significance is evaluated on the basis of a t-test between the resulting fitness value under the "ordered" versus random specification of correct policy choices.

the highest possible fitness levels or configurations close to the global optimum: in rugged landscapes, there are just too many positive-gradient paths that lead to local peaks other than the global one.

While the general pattern of results described above holds for both the hierarchical and centrality structure there are some differences, differences that are amplified when we consider the impact of historical constraints on policy choices below. In particular, the results regarding the final fitness value achieved under the ordered versus random specification of correct policy choices are quite similar for hierarchical and centrality structures. However, for the centrality structure, the *initial* value of fitness does not differ significantly between the random and ordered case until four policies are correctly specified. Thus, correctly presetting variables does, under the centrality interaction structure, seed the firm in a more attractive basin of attraction—that is, local tactical adjustments from this starting point lead on average to a superior local peak for all values of the number of policies set correctly; however, the direct benefit, in terms of initial fitness value, of presetting variables that are more strategic correctly is not as powerful within a centrality interaction structure as within a hierarchical interaction structure. In our subsequent analysis, we observe how tactical adjustments are able to compensate for potentially misspecified highly central policy choices whereas such adjustments are not possible for policies which have low levels of interactions with other policy choices—a property that helps resolve this difference between the results of **Table 1** and **Table 2**.

Strategic Mistakes and Tactical Mitigation

Success is not the only possible outcome to strategic prespecifications: they may also turn out to be mistakes. Alternatively, even if a policy choice made sense at one point in time, it may no longer be suited to an environment that has shifted and yet, if commitment-intensive, will be hard to reverse. The analysis in this subsection focuses on the downside rather than the upside of the effect of initial positioning in policy space. Specifically, it models the commitment-intensity or irreversibility of choices—perhaps their most basic temporal quality—by focusing on totally irreversible "mistakes" in the sense of policy variables whose values are preset to mismatch rather than match their values at the global optimum. The objective is to explore how the underlying structure of interactions among choices affects the residual costs of such mistakes, after local search aimed at tactical adjustment through both mitigation of these mistakes and efforts to align the full system of policy choices.

Table 3 summarizes the normalized fitness level achievable when each of the 15 possible policy variables is misspecified in the sense of being preset to a value inconsistent with its value at the global optimum.[11] The table also provides two tests of the statistical significance of the effect of more or less strategic important policies being misspecified. The first test for differences in performance contrasts the effect of misspecifying the ith policy versus its ith + 1 greater neighbor. The second test contrasts the effect of misspecifying the focal policy versus the least strategic 15th policy value. The former is the more stringent test of whether misspecifying a more or less strategic policy impacts final fitness since it focuses on whether a single increment in significance is significant, while the latter test uses the less demanding criterion of performance differences between misspecification of the focal policy and of the 15th policy.[12]

Under a hierarchical pattern of interactions, fitness improves markedly as the preset mismatch shifts from one of the higher-order variables to lower-level policy choices (note that a negative value for difference indicates that misspecifying the more strategic policy results in lower performance than misspecifying the less strategic policy) . The results are, however, quite different under a centrality interaction structure. In the i versus i+1 comparison, the evidence is mixed as to whether misspecifying more strategic policies results in reduced fitness (3 significant results of a positive difference and 3 significant results of a negative contrast), although the second test, contrasting the focal policy and the 15th policy, does provide fairly systematic evidence of such a misspecification penalty. Why might the preset mismatch of lower-order policy choices be comparatively more damaging to fitness levels under the centrality structure? Note that less central variables not only do not constrain, or substantially influence the payoff of many other choices, but they themselves are not greatly dependent upon other

[11] It does not make sense to explore a random specification of the misspecified policy as the analysis explores the impact, exhaustively, of different policies being misspecified.

policy choices. Being dependent on other policy choices facilitates mitigating shifts in policy variables other than the one that is preset—which there is reduced possibility of undertaking for less central choices.

Consistent with this effect, we see in **Figure 3** that firms operating under the constraints of legacy misspecifications often fail to end up in a policy configuration that would, from an unconstrained perspective, be internally consistent, i.e., constitute a local peak. (Furthermore, the configurations that do constitute local peaks are, on average, not particularly close to the global optimum: the average Hamming distance, or number of variables whose values differ across such local peaks and the global optimum, is approximately 4). The divergence between final configurations and (unconstrained) local peaks is particularly evident in the case of the centrality interaction structure. **Figure 3** indicates that with such a structure, a firm ends up at local peak, comprising an internally consistent set of choices across all 15 policy variables, roughly one-half the time when a more strategic policy is misspecified, but does so relatively rarely when less strategic policies are misspecified. A reasonable inference, explored more fully in the follow-up analysis, is that when a highly central policy is misspecified the firm builds an internally consistent set of policy choices compatible with this misspecification. That is, the other policy choices that are identified through local search form an consistent configuration of policies that are, in some sense, anchored by this misspecified policy. In contrast, when a less strategic policy is misspecifed, it seems that the firm frequently "accepts" this misspecification in a sense and builds a policy configuration that does not correspond to a local peak in the landscape.[13]

As a further robustness test of this result, a supplemental analysis was run in which the optimal configuration was identified subject to the constraint that one of the 15 policies is misspecified. This analysis helps clarify the extent to which the identification of a local peak is driven by the process of local search from a given starting position versus the global properties of the performance surface. The

---

[12] Obviously, for the case of the 14th policy, the two tests are identical.

percentages of local peaks in this analysis turned out to be nearly identical to those in the previous analysis, ranging from a value of 56% when the most strategic policy is misspecified to merely 5% when the least strategic policy is misspecified.[14] Furthermore, while the firm could always reduce the Hamming distance to the global optimum—the number of variables set to different values across the final policy configuration and the global optimum—to just 1, the firm does not, as a second-best, generally seek to minimize such distance. The Hamming distances between final policy configurations and the global peak range from an average value of 3.2 when the most strategic policy is misspecified to 1.2 when the least strategic policy is misspecified.

The role of relatively peripheral policy variables in this regard bears repeating. To the extent that a focal policy that is misspecified is dependent on or influences other policies, compensating changes in these other policies can be made that facilitate a distinct, but nevertheless reasonably effective constellation of policies. In contrast, when a relatively peripheral policy is misspecified under the centrality structure, the specification of the N-1 policy variables identified through a process of tactical adjustment tend not to correspond to a local peak (i.e., a consistent set of policy choices). Rather, the firm in some sense accepts this misspecification.

Modes of Interaction: Influence, Dependency, and Autonomy

Table 3 and **Figure 3** taken together suggest that the misspecification of a highly dependent policy does not impose the same performance costs as the misspecification of other variables. Indeed, there appears to be a certain robustness associated with dependent variables (see Siggelkow 2002b for a similar argument). Our analysis of interaction structures up to this point somewhat conflates the role of influence

[13] All the policy configurations that are reached, by definition, correspond to a local peak in the partial landscape consisting of the 14 policies that are free to vary. The issue addressed in Figure 3 is whether such a configuration corresponds to a local peak in full space of 15 policy variables.
[14] However, in contrast to the outcome under the process of local search, when a constrained optimum is calculated, the performance achieved when a more strategic policy is misspecified is statistically inferior to the performance achieved when a less strategic policy is specified.

and dependency in that policies that are relatively less dependent also tend to be less influential.[15] In **Table 4,** we consider an extreme adjacency matrix that disentangles these effects. We specify the first five policy variables to be influential with probability 1 and not dependent with probability 1 as well (i.e., r = 1 and p = 1). Analogously, we specify policies 6 to 10 as being influential with probability 0 and dependent with probability 1 (i.e., r = 0 and p = 1). The remaining five policies (policies 11 to 15) are treated as being autonomous (i.e., p = 0).

This stylized interaction structure allows us to tease out the underlying forces in the results we observe with the hierarchical and centrality interaction patterns. **Table 4** confirms that constraining one of the “influential” variables to differ from the global maximum has a profound effect on the relative fitness level that is achieved. Somewhat more surprisingly, constraining the autonomous variables to differ from the global optimum has a larger impact than constraining the seemingly more important “dependent” variables. The reason for this is that the presence of dependency allows for the possibility of substituting or compensating changes in policy variables. While tightly linked interaction patterns have generally been viewed as fragile, they also allow, through equifinality, for a certain robustness. In contrast, when an autonomous variable is misspecified, that has no negative implications for other choice variables; at the same time, however, there is no opportunity to compensate for any misspecification.

The parsing out of effects in this stylized adjacency matrix also offers greater room for optimism about the power of high-level strategy-making. The final column in **Table 4** tracks normalized fitness levels as an increasing number of variables are preset to match their values at the global maximum, with the remaining variables identified through a process of local search. The results suggest that it is sufficient to specify the purely influential variables correctly and then to follow up with a process of local search. The dependent variables are likely to be correctly specified if the influential variables are set to the global optimum, and the autonomous variables, as non-contextualized choices, can readily be set at their

---

[15] Specifying the interaction structures solely by varying p^H and p^C would not eliminate such confounding effects. Variation in these parameters not only affects influence and dependency, but also the level of autonomy or

optimum value via a process of local search. In that sense, at least, the intuition of the sufficiency of "grand strategy-making" and the presumption that operating details can safely be left unspecified are validated. It is the intertwining of influence and dependency—particularly with the centrality interaction structure—that prevents such top-level strategy-making from proving sufficient.

5. Robustness

It is important to consider the robustness of the analyses presented in the previous section. The prior analyses are based on the averaged results from 100 independent runs for each of 100 distinct adjacency matrices. That is, for each set of *p* and *r* values, 100 distinct adjacency matrices are drawn. For each realization of one of these adjacency matrices, 100 distinct randomly seeded fitness landscapes are specified; thus, each of these 100 landscapes shares a common structure of interdependencies, but varies in terms of the actual performance values associated with different configurations of policy choices. While these computations should allay concerns about robustness related to random effects, questions of robustness may remain with respect to the parameters of the model. In order to address them, it is useful to start out by noting that there are essentially 3 structural parameters: *r, p,* and *N.*[16] The analysis above explored landscape structures in which either *r* or *p* was held fixed at 0.5 and the other parameter varied from 0 to 1 among the *N* policy variables. As part of a structural robustness analysis check, it is important to examine how these results might change if the conditioning parameter assumes values other than 0.5.[17] The qualitative effects of the hierarchical position or centrality of a policy variable on the results of searching from a partially specified optimum or a constrained suboptimum are quite robust to different

---

interdependence. Thus, the analysis in this section is an important supplement to the prior analysis, but not a substitute.

[16] One could also explore alternatives to the uniform distribution for seeding the landscape; however, prior analysis (Kauffman 1993; Rivkin 1997) indicate that the analysis of landscapes tends to be quite robust to the specification of alternative distributions for the random variate.

[17] We have also examined the robustness of our results as *N* varies. Examining large values of *N* is extremely computationally intensive as the set of possible fitness values that need to be considered grows exponentially with *N.* We have re-analyzed our results for a range of *N* values and the qualitative effects of *r* and *p* (hierarchy and centrality) remain unchanged. The one qualitative effect of larger *N* that is evident is that it tends to reduce performance across all settings as the global peak increases relative to realized fitness.

baseline settings of *r* and *p.* The magnitude of the effects we identify decline (rise) for lower (higher) baseline values of *r* and *p* (again, bear in mind, the analysis consists of anchoring one parameter, for instance *r,* and varying the other parameter, in this case *p* values for individual policy choices) and to a lesser degree statistical significance. Low values of these parameters result in relatively simple fitness landscapes that pose less of a challenge to the problem of identifying strategic configurations and hence generate less variance and higher performance relative to the global peak, while higher values of the baseline parameter generate more complex landscapes that more sharply highlight the distinct experimental settings in the analysis.

Numerous other extensions to the basic analysis could be attempted. Given the simplicity of the temporal dimension of our modeling effort (which assumed the total irreversibility of specific variables), we did not discuss degrees of irreversibility, although differences in this regard might supply an additional useful marker of influence. Similarly, even though we did not allow the weights on (the direct effects of) choices to vary, it is clear that that is another key indicator of influence in the real world, either individually or in interaction with irreversibility (see Solow, *et al.* 2002 for an examination of this form of heterogeneity). Such extensions would, however, constitute a distinct modeling exercise rather than an examination of the robustness of the current specification.

6. Conclusion

Some choices condition other choices. This conditioning may be synchronic, as implied by the activity systems approach, or diachronic, as in models of path dependence and commitment. This paper was motivated by the idea that it would be useful for the strategy field to move beyond rhetorical appeals regarding the relative importance of one set of "linkages" or another. This task will require both more carefully specified theoretical models that embody both sets of linkages, as well as empirical work that is fine-grained enough to permit exploration of the nuances of choice structures (cf., Siggelkow 2002a). The current analysis is clearly targeted primarily at the former goal.

We find that it is useful to distinguish the degree to which choices are autonomous, influential, or dependent. Autonomous choices are choices that are disconnected from others. In relation to such choices—but not others—the notion of universal best practices makes some sense. Note that while getting these choices wrong does not, by definition, alter the payoffs from other choices, it is also true that these kinds of choices, if wrong, cannot be compensated for by dependent choices. Still, such choices can be made independently of an overarching choice of strategy and therefore have the quality of operational policies (Porter 1996).

Similar considerations sometimes also apply to groups of choices, as in the (nearly) decomposable systems originally highlighted by Simon (1962) and recently analyzed in the business context with an NK approach by Ethiraj and Levinthal (2003) and Rivkin and Siggelkow (forthcoming) among others. At the limit, a subsystem of choices that do not interact with any choices outside the subsystem can be treated like an individually autonomous choice: partitioned and made on standalone terms. The implied reduction in the complexity of the overall choice problem tends to be significant.

Choices that are not autonomous or decomposable, in contrast, should not be treated symmetrically—as they are by the canonical NK model—as having equal potential to be influential. As our examination of examples suggested, it is important to recognize both the multiplicity of choices (or themes) and the fact that some of them matter more than others. Our modeling effort set up two cross-sectional alternatives to the random interaction model of NK landscapes that encompassed variations in individual choice elements' interactions with others: hierarchy and centrality. The initial analysis of strategy-making confirmed, under the assumption that choices are of symmetric weight but asymmetric in their interactions, that correctly prespecifying policy choices that are more strategic provides more leverage than correctly prespecifying less strategic or arbitrary policies. However, the requirements as to the proportion of policy choices that need be specified correctly to reach the global optimum remain daunting.

The results regarding the constraints of history—preset mismatches rather than matches—also revealed the salience, although here in a negative sense, of more strategic variables under the hierarchical interaction structure. However, with importance determined by degree of centrality, more puzzling results were observed. The subsequent analysis of the pure effects of influence, dependency, and autonomy helped to unpack this puzzle. In characterizing the initial matrices of interaction, as we varied the parameter r, we changed both the likelihood that a policy is influential and, conversely, the degree to which it is dependent. As a result, the interaction structures depicted in **Figures 2a** and **2b,** for example, had a more complex structure than may have been apparent at first. Separating out the effects of influence, dependency, and autonomy brought dependent choices—choices that are more influenced than influential—into particularly sharp focus. The modeling effort indicated that such choices can afford two very distinct types of benefits: enabling the more effective pursuit of the strategy implied by higher-order choices by aligning with them, and mitigating the effects of higher-order handicaps. In other words, dependent choices can be either advantage-seeking or disadvantage-mitigating, although the first role is the one that is typically stressed in the literature on strategy. The kind of policy configurations associated with disadvantage mitigation often do not correspond to (unconstrained) local peaks in the performance landscape. By implication, the standard strategic test of internal consistency at a point in time cannot be applied independently of dynamic considerations, because optimal adjustment over time to constraints may result in what looks like an internally inconsistent set of choices from a purely static perspective.

Strategic positions unfold over time. That unfolding may reflect the elaboration of some initial strategic choices, or the temporal resolution of a strategic position may reflect efforts to establish an effective position subject to some historical constraints on one or more policy choices. The impact of these diachronic linkages is importantly mediated by the presence of synchronic linkages. In the absence of linkages across policy choices, the sequential search for a optimal policy configuration is trivial. Conversely, in the absence of dependency relations among policy choices, there is no opportunity to accommodate and mitigate the effect of a historically constrained and misspecified policy. It is the conjunction of the synchronic and the diachronic that underlies the complexity of strategy formation and it is some insight into their joint consequences that we have tried to offer.

References

Andrews, K. 1971. *The Concept of Corporate Strategy.* Richard D. Irwin: Homewood, IL.

Arrow, K. J. 1964. Optimal capital policy, the cost of capital, and myopic decision rules. *Annals of the Institute of Statistics and Mathematics* **16** 21–30.

Baldwin, C., K. Clark 2000. *Design Rules: The Power of Modularity.* MIT Press, Cambridge, MA.

Barney, J. B. 1997. *Gaining and sustaining competitive advantage*. Addison-Wesley: Reading, MA.

Bellman, R. 1957. *Dynamic Programming*. Princeton University Press: Princeton, NJ.

Burgelman, R. 1994. Fading memories: A process theory of strategic business exits. *Administrative Science Quarterly* **39** 24–56.

Caves, R. 1980. Industrial organization, corporate strategy and structure. *Journal of Economic Literature* **18** 64–92.

Cyert, R. M., J. G. March. 1963. *A Behavioral Theory of the Firm*. Prentice-Hall: Englewood Cliffs, NJ.

Ethiraj, E., D. Levinthal. 2004. Modularity and innovation in complex systems. *Management Science* **50** 159–173.

2005. Bounded rationality and the search for organizational architecture: An evolutionary perspective on the design of organizations and their evolvability. *Administrative Science Quarterly* **49** 404–437.

Gavetti, G., D. Levinthal. 2000. Looking forward and looking backward: Cognitive and experiential search. *Administrative Science* March 2000.

Ghemawat, P. 1991. *Commitment.* Free Press: New York.

1998. Competition and business strategy in historical perspective. Harvard Business School Press: Boston MA. HBSP #798-010.

1999. *Strategy and the Business Landscape*. Addison-Wesley: Reading, MA.

Kauffman, S. 1989. Adaptation on rugged fitness landscapes. In D. Stein (Ed.), *Lectures in the Sciences of Complexity*. Addison-Wesley: Reading, MA.

1993. *The Origins of Order: Self-organization and Selection in Evolution.* Oxford University Press: New York.

Levinthal, D. 1997. Adaptation on rugged landscapes. *Management Science* **43(**7) 934–950.

Lenox, M. J., S. F. Rockart, A. J. Lewin. 2005. Interdependency, competition and the distribution of firm and industry profits. *Management Science* forthcoming.

Lewis, A. 1985. On effectively computable realizations of choice functions. *Mathematical Social Sciences* **10** 43–80.

MacCormack, A., J. Rusnak, C. Y. Baldwin. 2004. Exploring the structure of complex software designs: An empirical study of open source and proprietary code. *Harvard Business School Working Paper Series* No. 05-016.

March, J., H. Simon. 1958. *Organizations*. John Wiley & Co.: New York.

Milgrom, P., J. Roberts. 1990. The economics of modern manufacturing: Technology, strategy, and organization. *American Economic Review* **80**(3) 511–528.

1995. The economics of modern manufacturing: Reply. *American Economic Review* **85**(4) 997.

Miller, K. 2002. Knowledge inventories and managerial myopia. *Strategic Management Journal* **23** 689–706.

Mintzberg, H. 1978. Patterns in strategy formulation. *Management Science* **24** 934–948.

Porter, M. E. 1996. What is strategy? *Harvard Business Review.* November-December 61–78.

Rivkin, J. W. 1997. *Consequences of Fit*. Unpublished Ph.D. dissertation, Harvard University.

2000. Imitation of complex strategies. *Management Science* **46** 824–844.

Rivkin, J. W., N. Siggelkow. 2003. Balancing search and stability: Interdependencies among elements of organizational design. *Management Science* **49** 290–321.

Forthcoming. Patterned interactions in complex systems: Implications for exploration. *Management Science*.

Sharman, D. M., A. A. Yassine. 2004. Characterizing complex product architectures. *Systems Engineering Journal* **7**(1) 35–60.

Siggelkow, N. 2001. Change in the presence of fit: The rise and fall, and the resurgence of Liz Claiborne. *Academy of Management Journal* **44** 838–858.

2002a. Evolution towards fit. *Administrative Science Quarterly* **47** 125–159.

2002b. Misperceiving interactions among complements and substitutes: Organizational consequences. *Management Science* **48** 900–917.

Simon, H. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics* **69** 99–118.

1962. The architecture of complexity. *Proceedings of the American Philosophical Society* **106** 467–482.

Solow, D., A. Burnetas, T. Roeder, N. Greenspan. 1999. Evolutionary consequences of selected locus-specific variations in epistasis and fitness contribution in Kauffman's *NK* Model. *Journal of Theoretical Biology* **196** 181–196.

Sussman, H. J. 1975. Catastrophe theory. *Synthese* **31**(2) 4.

Teece, D., G. Pisano. 1994. The dynamic capabilities of firms: An introduction. *Industrial and Corporate Change* **3** 537–556.

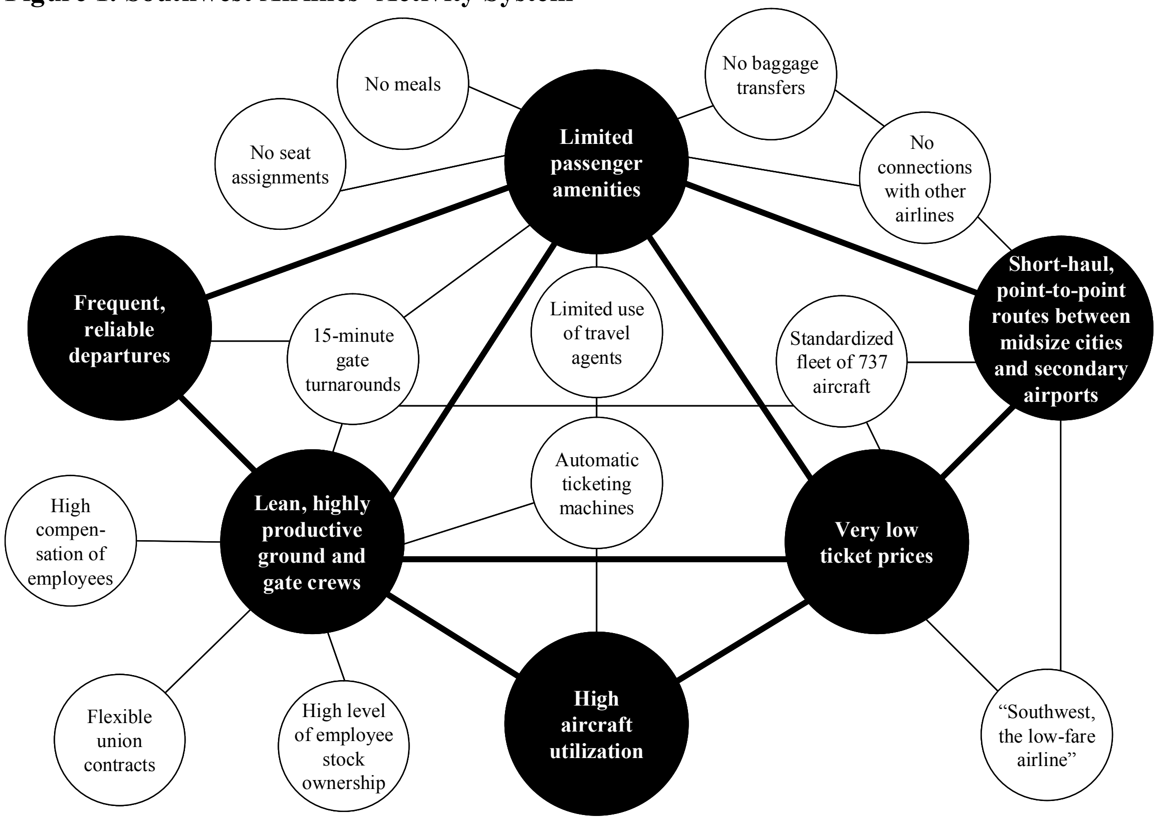
Topkis, D. M. 1978. Minimizing a submodular function on a lattice. *Operations Research* **26(**2) 305–331.

1995. Comparative statics of the firm. *Journal of Economic Theory* **67(**2) 370–401.

Weinberger, E. 1991. Local properties of Kauffman's N-K Model: A tunably rugged energy landscape. *Physical Review A* (**44**) 6399–6413.

Wright, S. 1931. Evolution in Mendelian populations. *Genetics* **16** 97–159.

Figure 1. Southwest Airlines' Activity System



Source: Porter 1996.

Figure 2a. Hierarchy with High Interdependency

	1	2	3	4	5	6	7	8	9	10
1	1	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	1	1	1	0	0	0	0	0	0	0
4	1	1	1	1	0	0	0	0	0	0
5	1	1	1	1	1	0	0	0	0	0
6	1	1	1	1	1	1	0	0	0	0
7	1	1	1	1	1	1	1	0	0	0
8	1	1	1	1	1	1	1	1	0	0
9	1	1	1	1	1	1	1	1	1	0
10	1	1	1	1	1	1	1	1	1	1

Figure 2b. Centrality with High Interdependency

	1	2	3	4	5	6	7	8	9	10
1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	0
3	1	1	1	1	1	1	1	1	0	0
4	1	1	1	1	1	1	1	0	0	0
5	1	1	1	1	1	1	0	0	0	0
6	1	1	1	1	1	1	0	0	0	0
7	1	1	1	1	0	0	1	0	0	0
8	1	1	1	0	0	0	0	1	0	0
9	1	1	0	0	0	0	0	0	1	0
10	1	0	0	0	0	0	0	0	0	1

Figure 2c. Hierarchy with Low Interdependency

	1	2	3	4	5	6	7	8	9	10
1	1	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	0	1	1	0	0	0	0	0	0	0
4	0	1	1	1	0	0	0	0	0	0
5	1	1	0	1	1	0	0	0	0	0
6	0	1	1	1	0	1	0	0	0	0
7	1	0	0	1	1	1	1	0	0	0
8	1	1	1	0	1	0	0	1	0	0
9	1	0	1	1	0	1	1	0	1	0
10	1	0	1	0	1	0	1	1	1	1

Figure 2d. Centrality with Low Interdependency

	1	2	3	4	5	6	7	8	9	10
1	1	0	0	1	1	0	1	0	1	1
2	0	1	1	0	1	1	0	1	0	0
3	1	0	1	0	1	0	0	1	0	0
4	0	1	0	1	0	1	1	0	0	0
5	1	1	0	0	1	0	0	0	0	0
6	1	0	1	0	0	1	0	0	0	0
7	0	1	0	1	0	0	1	0	0	0
8	1	0	1	0	0	0	0	1	0	0
9	0	1	0	0	0	0	0	0	1	0
10	1	0	0	0	0	0	0	0	0	1

Figure 3: Final Policy Configurations

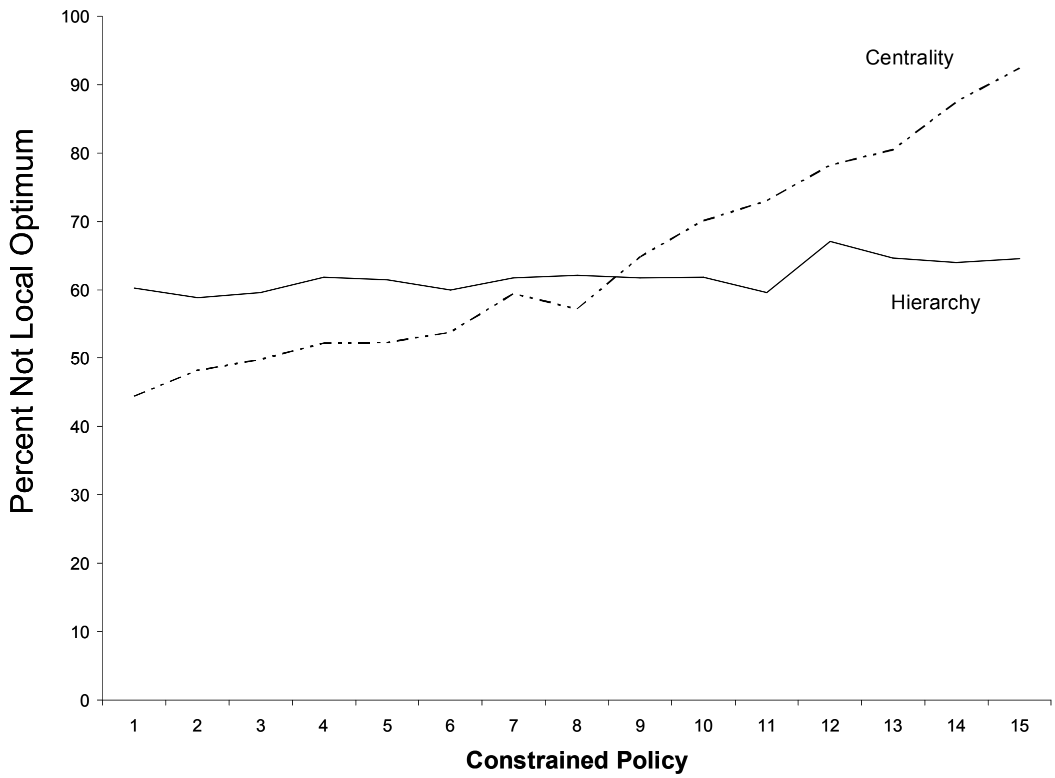


Table 1: Value of Partially Articulated Activity Map with Hierarchical Structure†

	Ordered			Random		
Number of Policies	Initial Value	Number of Steps	Final Fitness	Initial Value	Number of Steps	Final Fitness
1	.7287*	6.6422	0.9731	.7256*	6.6551	0.9729
	(.0920)	(2.2727)	(.0334)	(.0935)	(2.2587)	(.0335)
2	.7463**	6.2023	.9771**	.7387**	6.1959	.9758**
	(.0897)	(2.1614)	(.0309)	(.0932)	(2.1915)	(.0325)
3	.7630**	5.7824	.9807**	.7511**	5.8262	.9788**
	(.0878)	(2.0198)	(.0287)	(.0933)	(2.0592)	(.0311)
4	.7814**	5.3181	.9840**	.7663**	5.3560	.9820**
	(.0856)	(1.9235)	(.0261)	(.0911)	(1.9686)	(.0293)
5	.7997**	4.8830	.9875**	.7814**	4.9093	.9852**
	(.0827)	(1.7914)	(.0237)	(.0911)	(1.8704)	(.0266)
6	.8181**	4.4264	.9901**	.7979**	4.4298	.9883**
	(.0800)	(1.6706)	(.0209)	(.0898)	(1.7371)	(.0242)
7	.8366**	3.9486	.9926**	.8128**	3.9714	.9909**
	(.0774)	(1.5591)	(.0180)	(.0884)	(1.6207)	(.0216)
8	.8558**	3.4782	.9948**	.8339**	3.4573	.9925**
	(.0731)	(1.4280)	(.0153)	(.0857)	(1.4803)	(.0200)
9	.8769**	2.9761	.9965**	.8524**	2.9978	.9949**
	(.0683)	(1.2904)	(.0126)	(.0821)	(1.3470)	(.0133)
10	.8962**	2.5043	.9978**	.8731**	2.5010	.9967**
	(.0629)	(1.1985)	(.0100)	(.0775)	(1.2090)	(.0133)
11	.9182**	1.9874*	.9987**	.8952**	2.0122*	.9981**
	(.0569)	(1.0436)	(.0077)	(.0727)	(1.0576)	(.0097)
12	.9386**	1.5047	.9994**	.9188**	1.5044	.9989**
	(.0487)	(.8924)	(.0049)	(.0654)	(.8979)	(.0077)
13	.9579**	1.0224**	0.9997	.9452**	0.9970**	0.9997
	(.0405)	(.7259)	(.0035)	(.0557)	(.7226)	(.0040)
14	.9789**	0.4990	1.0000	.9721**	0.4926	1.0000
	(.0294)	(.5000)	(0.0000)	(.0410)	(.4999)	(0.0000)
15	1.0000	0.0000	1.0000	1.0000	0.1390	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

† * indicates $p < .01$ and ** $p < .005$; standard deviations are provided in parentheses.

Table 2: Value of Partially Articulated Activity Map with Centrality Structure†

	Ordered			Random		
Number of Policies	Initial Value	Number of Steps	Final Fitness	Initial Value	Number of Steps	Final Fitness
1	.7194	6.9004	.9744**	.7203	6.9017	.9714**
	(.0950)	(2.3397)	(.0340)	(.0951)	(2.4119)	(.0356)
2	.7331	6.4701*	.9795**	.7335	6.4166**	.9745**
	(.0949)	(2.2014)	(.0313)	(.0935)	(2.3066)	(.0346)
3	.7469	6.0251**	.9836**	.7473	5.9333**	.9780**
	(.0947)	(2.0981)	(.0290)	(.0939)	(2.1717)	(.0332)
4	.7644**	5.5145	.9886**	.7614**	5.4999	.9816**
	(.0933)	(1.9086)	(.0242)	(.0919)	(2.0423)	(.0309)
5	.7833**	5.0197	.9917**	.7769**	5.0450	.9844**
	(.0922)	(1.7793)	(.0204)	(.0906)	(1.9245)	(.0286)
6	.7999**	4.5404	.9944**	.7931**	4.5224	.9872**
	(.0905)	(1.6390)	(.0169)	(.0888)	(1.7841)	(.0261)
7	.8230**	4.0265	.9965**	.8122**	4.0271	.9897**
	(.0870)	(1.5151)	(.0135)	(.0881)	(1.6614)	(.0241)
8	.8488**	3.5004**	.9979**	.8288**	3.5574**	.9925**
	(.0803)	(1.3775)	(.0153)	(.0860)	(1.5240)	(.0209)
9	.8721**	3.004*	.9988**	.8486**	3.0418*	.9948**
	(.0749)	(1.2784)	(.0101)	(.0832)	(1.3864)	(.0175)
10	.8966**	2.4945*	.9997**	.8704**	2.5254*	.9965**
	(.0676)	(1.1327)	(.0077)	(.0768)	(1.2199)	(.0146)
11	.9204**	2.0054	.9998**	.8931**	2.0273	.9980**
	(.0578)	(1.0084)	(.0039)	(.0735)	(1.0914)	(.0111)
12	.9426**	1.4944*	1.0000**	.9165**	1.5216*	.9990**
	(.0486)	(.8706)	(0.0000)	(.0672)	(.8995)	(.0075)
13	.9635**	.9978	1.0000**	.9438**	.9993	.9996**
	(.0377)	(.7136)	(0.0000)	(.0575)	(.7303)	(.0049)
14	.9817**	.4959	1.0000	.9703**	.5000	1.0000
	(.0269)	(.5000)	(0.0000)	(.0430)	(.5000)	0.0000
15	1.0000	0.0000	1.0000	1.0000	0.0000	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

† * indicates p < .01 and ** p < .005; standard deviations are provided in parentheses.

Table 3: Constraints of History†

Policy Mis-specified	Final Fitness	Hierarchy Difference (i vs. i + 1)	Difference (i vs. 15)	Final Fitness	Centrality Difference (i vs. i + 1)	Difference (i vs. 15)
1	.9308 (.0447)	-.0016**	-.0148**	.9377 (.0425)	-.0015**	.0006
2	.9324 (.0447)	-.0019**	-.0133**	.9392 (.0414)	.0003	.0021**
3	.9343 (.0432)	.0006	-.0114**	.9389 (.0419)	.0010*	.0018**
4	.9337 (.0440)	-.0034**	-.0120**	.9378 (.0416)	-.0007	.0008
5	.9370 (.0421)	.0014*	-.0086**	.9385 (.0419)	.0070	.0014*
6	.9356 (.0429)	-.0022**	-.0100**	.9378 (.0421)	.0070	.0008
7	.9379 (.0418)	-.0012*	-.0078**	.9371 (.0423)	-.0024**	0.0000
8	.9390 (.0414)	-.0008	-.0066**	.9395 (.0412)	.0002	.0024**
9	.9398 (.0411)	-.0016**	-.0058**	.9392 (.0415)	.0012*	.0022**
10	.9414 (.0400)	-.0004	-.0042**	.9380 (.0420)	-.0001	.0009
11	.99418 (.0395)	.0002	-.0038**	.9381 (.0416)	.0009	.0011*
12	.9416 (.0402)	-.0020**	-.0040**	.9373 (.0421)	-.0023**	.0002
13	.99436 (.0392)	-.0014**	-.0020**	.9396 (.0418)	.0018**	.0025**
14	.9450 (.0387)	-.0006	-.0006	.9377 (.0421)	.0007	.0007
15	.9456 (.0385)	0.0000	0.0000	.9371 (.0424)	0.0000	0.0000

† * indicates p < .01 and ** p < .005; standard deviations are provided in parentheses.

Table 4: Extreme Adjacency Matrix†

	Policy Mis-specified	Final Fitness	Constraints of History: Fitness – Avg. Influence	Constraints of History: Fitness – Avg. Dependent	Constraints of History: Fitness – Avg. Independent	Fitness with partial activity map
Influential	1	.9212 (.0483)		-.0150**	.0019**	.9590 (.0454)
	2	.9216 (.0480)		-.0146**	.0023**	.9692 (.0423)
	3	.9222 (.0480)		-.0141**	.0029**	.9802 (.0367)
	4	.99214 (.0483)		-.0148**	.0022**	.9929 (.0227)
	5	.99219 (.0479)		-.0144**	.0026**	1.0000 (0.0000)
Dependent	6	.9368 (.0439)	-.0152**		.0175**	1.0000 (0.0000)
	7	.9356 (.0454)	-.0139**		.0163**	1.0000 (0.0000)
	8	.9365 (.0440)	-.0148**		.0172**	1.0000 (0.0000)
	9	.9364 (.0441)	-.0147**		.0171**	1.0000 (0.0000)
	10	.9359 (.0446)	-.0142**		.0166**	1.0000 (0.0000)
Independent	11	.9194 (.0510)	-.0023**	-.0169**		1.0000 (0.0000)
	12	.9193 (.0509)	-.0023**	-.0169**		1.0000 (0.0000)
	13	.9196 (.0612)	-.0021**	-.0167**		1.0000 (0.0000)
	14	.9196 (.0633)	-.0021**	-.0167**		1.0000 (0.0000)
	15	.9186 (.0645)	-.0030**	-.0176**		1.0000 (0.0000)

† * indicates p < .01 and ** p < .005; standard deviations are provided in parentheses.