Choice Interactions and Business Strategy

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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 fitness landscapes 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.

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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 and Pisano 1994). But although 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.

This line of analysis fits with growing interest in finding a constructive middle ground between hardcore rational accounts of strategy making and more behavioral, emergent accounts. Our first set of analyses provides a useful platform for such a dialogue and offers some intriguing initial results. In general,

the demands on ex ante strategy making are quite daunting with respect to the degree to which such ex ante strategy would have to be prespecified correctly. However, our analysis of a range of interaction structures provides an important qualification to this conclusion. If there is a set of influential policy choices that have a strict hierarchical relationship with respect to other policy choices, then it is sufficient that this subset of variables be specified correctly to ensure an optimal policy configuration.

The other set of results pertains to the implications of possible constraints and commitments associated with some subset of policy choices. A critical question here is whether such constraints lead to an entirely distinct, internally consistent bundle of choices (a distinct local peak) or whether such constraints lead to strategies that maximally approximate the globally optimal strategy, subject to the imposed constraint. In general, when policy choices both depend on other choices, in addition to influencing them, such a constraint leads to the emergence of a wholly distinct configuration, often quite far from the global optimum. However, the performance "penalty" is, by the same token, attenuated by the fact that unconstrained policy choices can mitigate the negative impact of a policy constrained to differ from the value associated with the first-best optimum. Conversely, relatively independent or autonomous policies, when constrained to be misspecified, result in configurations that are not internally consistent but are closer in distance to the globally optimal strategy. Yet these misspecifications result in higher performance penalties because autonomous policies do not provide an opportunity for compensatory changes in other policies to mitigate the impact of such misspecification.

The following section examines the nature of interdependencies among strategy choices and, in particular, links the conceptual framework of activity systems to a more general matrix structure that allows for directional interdependencies. We then provide a formal representation of these ideas and characterize the full model structure and results.

2. From Activity Systems to Adjacency Matrices

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. 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 and Pisano 1994 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 multidimensional 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. What this treatment emphasizes is that, although 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 guide the firm toward a relatively effective position within its 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 vectors of strategy 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 subsystem of a firm's strategy, such as its product positioning, becomes fully characterized, and then, in a sequential manner, other "subsystems" 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 various patterns of interaction is suggested by the observation that activity systems bear 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 1 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, although there is a resemblance between activity systems of the sort depicted in Porter (1996) 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 as characterized in depictions of activity systems): the focus here is on identifying the choices that are strategic in terms of their interactions with other choices instead of presorting them independent 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 second enhancement, of allowing for directionality in linkages, is necessary only if adjacency matrices 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.

To provide an initial intuition for such structures, it is useful to consider the literature on product design, which has developed design structure matrices that are formally equivalent to the adjacency matrices considered here. For instance, MacCormack et al. (2004) offer a clear illustration of an asymmetric relationship in the context of computer programming.[2] More generally, analyses of interactions in actual technical

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

[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 subroutine), "this creates a dependency between the two source files [programs] in a *specific* (italics in the original) direction. For example, if Sourcefile1 calls Function A,

Figure 1a   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 1c   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 1b   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 1d   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

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]

In a strategic context, reconsider the example of Vanguard. 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] Because the company was a true mutual, admin-

istrative 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, there appears to be significant asymmetry in the policy choices characterizing the Vanguard activity system with some policies, such as the organizational structure, having a hierarchical relationship with other policies, such as the choice of product focus.

We therefore allow for directionality in linkages by distinguishing between influence and dependence and 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

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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 et al. 2004, p. 9).

[3] Rivkin and Siggelkow (2007) 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.

[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.

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 it is 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 is the ability to allow for the sequencing of choices. Sequential dependency relationships have been highlighted by Thompson (1967) and are also considered in the literature on design structure matrices, 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 1's 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.

Despite this last simplification, the structure of choices implied by this structure admits a wide range of interactions. 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 1a–1d span a wide range of patterns of interactions. Figure 1a is a relatively hierarchical matrix in that elements (policies) that are very influential tend not to depend on other elements, whereas Figure 1b 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 1c and 1d display systems that are relatively hierarchical and relatively symmetric, respectively, but with much lower levels of interdependence than in Figures 1a and 1b. 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 pairwise complementary for all values of the choice variables involved and for all values of other choice variables. Topkis (1978, 1995) and Milgrom and Roberts (1990, 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 because the values of relevant variables change. 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, 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 of 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 the usual depiction of activity systems (cf. Porter 1996). To remedy this defect, we need more degrees of freedom than are afforded by a single interactivity parameter, K. This is precisely what adjacency matrices of the sort discussed above afford: the ability to vary in the degree to which choices influence or are influenced by others.

As suggested earlier, 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) and 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 1a 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.

In contrast, for instance, the Southwest activity system depicted by Porter (1996) 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 1b 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 nine other choices, is the most central, choice 2 the second most central, and so on.

It is important to add that asymmetric interaction matrices are consistent with symmetric interdependencies in overall payoff values. Consider a two-policy system with each policy taking on a binary value. If the returns to the first policy depend on the second policy, then $V(0,0) - V(1.0) \neq V(0,1) - V(1,1)$. Similarly, if the returns to the second policy depend on the first policy, then $V(0,0) - V(0,1) \neq V(1.0) - V(1,1)$. However, this symmetric relationship of dependency does not imply that the associated interaction matrix is symmetric.[5]

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 toward 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.[6] Thus, by varying r_i from 0 to 1 we specify the relative degree to which a policy is dependent or influential, and by varying p_i from 0 to 1 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, and the other examines the heterogeneity among choices with respect to the centrality of interactions. To 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 $1/N$ 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[7]) and varying the

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[5] We thank Jan Rivkin and Nicolaj Siggelkow for helping suggest this point. For a rigorous demonstration, see the online supplement, which is provided in the e-companion (http://mansci.journal.informs.org/).

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

[7] In separate analyses not reported here, we have considered a wide range of "base-case" values for both r and p. 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

value of p from 1 to $1/N$ in increments of $1/N$. There-fore, 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 has a value of p of $(1-1/N)$ and a value of r of r_0, and so on.[8]

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.[9] 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 $f(x_i \mid x_{i1}, x_{i2}, \ldots, x_{iK_i})$. Therefore, each element's pay-off 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 distribution from 0 to 1 to each possible $f(x_i \mid x_{i1}, x_{i2}, \ldots, x_{K_i})$ combination, with the overall fitness value then being defined as $\sum_{i=1 \text{ to } N} f(x_i \mid x_{i1}, x_{i2}, \ldots, x_{iK_i})/N$.

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. Although 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, work by Weinberger (1991) and others suggests that the structure of the fitness landscape is not very 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.[10] Although 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 although 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. 2007). 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 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

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constrained suboptimum turn out to be quite robust to different baseline settings of r and p. The magnitude of the effects we identify decline (rise) for lower (higher) baseline values of r and p as does, 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, whereas higher values of the baseline parameter generate more complex landscapes that more sharply highlight the distinct experimental settings in the analysis.

[8] 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 nondiagonal 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 nondiagonal values of the 225 entries in the 15×15 adjacency matrix.

[9] 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).

[10] The focus of their work is to demonstrate that sufficiently extreme weighting differences, in particular weighting the contribution of one policy by $1 - \varepsilon$ and the other $N - 1$ variables by ε for sufficiently small values of ε, can allow a process of local search to reach the global optimum even under conditions of high interaction (K) across policy choices.

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 fitness value 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 examine the 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 prior competitive settings?

4.1. Strategic Guidance and Tactical Alignment
How might a complex policy system 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 of a high dimensionality seems daunting; at the same time, it seems unlikely to be purely emergent. A plausible picture of managerial processes seems to be that although 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 the emergence of strategic positions that is central to "process" discussions of strategy formulation (Mintzberg 1978, Burgelman 1994).

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 of the circles in a map of an activity system), 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 an activity map, 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 of the other policy vectors that differ from the current vector in

Table 1   Value of Partially Articulated Activity Map with Hierarchical Structure

Number of policies	Ordered			Random		
	Initial value	Number of steps	Final fitness	Initial value	Number of steps	Final fitness
1	0.7287* (0.0920)	6.6422 (2.2727)	0.9731 (0.0334)	0.7256* (0.0935)	6.6551 (2.2587)	0.9729 (0.0335)
2	0.7463** (0.0897)	6.2023 (2.1614)	0.9771** (0.0309)	0.7387** (0.0932)	6.1959 (2.1915)	0.9758** (0.0325)
3	0.7630** (0.0878)	5.7824 (2.0198)	0.9807** (0.0287)	0.7511** (0.0933)	5.8262 (2.0592)	0.9788** (0.0311)
4	0.7814** (0.0856)	5.3181 (1.9235)	0.9840** (0.0261)	0.7663** (0.0911)	5.3560 (1.9686)	0.9820** (0.0293)
5	0.7997** (0.0827)	4.8830 (1.7914)	0.9875** (0.0237)	0.7814** (0.0911)	4.9093 (1.8704)	0.9852** (0.0266)
6	0.8181** (0.0800)	4.4264 (1.6706)	0.9901** (0.0209)	0.7979** (0.0898)	4.4298 (1.7371)	0.9883** (0.0242)
7	0.8366** (0.0774)	3.9486 (1.5591)	0.9926** (0.0180)	0.8128** (0.0884)	3.9714 (1.6207)	0.9909** (0.0216)
8	0.8558** (0.0731)	3.4782 (1.4280)	0.9948** (0.0153)	0.8339** (0.0857)	3.4573 (1.4803)	0.9925** (0.0200)
9	0.8769** (0.0683)	2.9761 (1.2904)	0.9965** (0.0126)	0.8524** (0.0821)	2.9978 (1.3470)	0.9949** (0.0133)
10	0.8962** (0.0629)	2.5043 (1.1985)	0.9978** (0.0100)	0.8731** (0.0775)	2.5010 (1.2090)	0.9967** (0.0133)
11	0.9182** (0.0569)	1.9874* (1.0436)	0.9987** (0.0077)	0.8952** (0.0727)	2.0122* (1.0576)	0.9981** (0.0097)
12	0.9386** (0.0487)	1.5047 (0.8924)	0.9994** (0.0049)	0.9188** (0.0654)	1.5044 (0.8979)	0.9989** (0.0077)
13	0.9579** (0.0405)	1.0224** (0.7259)	0.9997 (0.0035)	0.9452** (0.0557)	0.9970** (0.7226)	0.9997 (0.0040)
14	0.9789** (0.0294)	0.4990 (0.5000)	1.0000 (0.0000)	0.9721** (0.0410)	0.4926 (0.4999)	1.0000 (0.0000)
15	1.0000 (0.0000)	0.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)	0.1390 (0.0000)	1.0000 (0.0000)

*$p < 0.01$, **$p < 0.005$; standard deviations are provided in parentheses.

Table 2   Value of Partially Articulated Activity Map with Centrality Structure

Number of policies	Ordered			Random		
	Initial value	Number of steps	Final fitness	Initial value	Number of steps	Final fitness
1	0.7194 (0.0950)	6.9004 (2.3397)	0.9744** (0.0340)	0.7203 (0.0951)	6.9017 (2.4119)	0.9714** (0.0356)
2	0.7331 (0.0949)	6.4701* (2.2014)	0.9795** (0.0313)	0.7335 (0.0935)	6.4166** (2.3066)	0.9745** (0.0346)
3	0.7469 (0.0947)	6.0251** (2.0981)	0.9836** (0.0290)	0.7473 (0.0939)	5.9333** (2.1717)	0.9780** (0.0332)
4	0.7644** (0.0933)	5.5145 (1.9086)	0.9886** (0.0242)	0.7614** (0.0919)	5.4999 (2.0423)	0.9816** (0.0309)
5	0.7833** (0.0922)	5.0197 (1.7793)	0.9917** (0.0204)	0.7769** (0.0906)	5.0450 (1.9245)	0.9844** (0.0286)
6	0.7999** (0.0905)	4.5404 (1.6390)	0.9944** (0.0169)	0.7931** (0.0888)	4.5224 (1.7841)	0.9872** (0.0261)
7	0.8230** (0.0870)	4.0265 (1.5151)	0.9965** (0.0135)	0.8122** (0.0881)	4.0271 (1.6614)	0.9897** (0.0241)
8	0.8488** (0.0803)	3.5004** (1.3775)	0.9979** (0.0153)	0.8288** (0.0860)	3.5574** (1.5240)	0.9925** (0.0209)
9	0.8721** (0.0749)	3.004* (1.2784)	0.9988** (0.0101)	0.8486** (0.0832)	3.0418* (1.3864)	0.9948** (0.0175)
10	0.8966** (0.0676)	2.4945* (1.1327)	0.9997** (0.0077)	0.8704** (0.0768)	2.5254* (1.2199)	0.9965** (0.0146)
11	0.9204** (0.0578)	2.0054 (1.0084)	0.9998** (0.0039)	0.8931** (0.0735)	2.0273 (1.0914)	0.9980** (0.0111)
12	0.9426** (0.0486)	1.4944* (0.8706)	1.0000** (0.0000)	0.9165** (0.0672)	1.5216* (0.8995)	0.9990** (0.0075)
13	0.9635** (0.0377)	0.9978 (0.7136)	1.0000** (0.0000)	0.9438** (0.0575)	0.9993 (0.7303)	0.9996** (0.0049)
14	0.9817** (0.0269)	0.4959 (0.5000)	1.0000 (0.0000)	0.9703** (0.0430)	0.5000 (0.5000)	1.0000 (0.0000)
15	1.0000 (0.0000)	0.0000 (0.0000)	1.0000 (0.0000)	1.0000 (0.0000)	0.0000 (0.0000)	1.0000 (0.0000)

*$p < 0.01$, **$p < 0.005$; standard deviations are provided in parentheses.

terms of just one choice element. If a superior alternative is identified in the immediate neighborhood of the existing policy array, it is adopted.[11] 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 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 set-

tings 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 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 prespecified 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.[12] This superior initial "seeding" of the organization in the performance landscape, in turn,

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[11] 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 "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.

[12] 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.

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 the 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. Furthermore, specifying more strategic policies correctly has a statistically significant effect on the resulting performance. However, a high level of specificity is necessary to obtain 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.

Although 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 that have low levels of interactions with other policy choices—a property that helps resolve this difference between the results of Tables 1 and 2.

4.2. 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.[13] The table also provides two tests of the statistical significance of the effects 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 because it focuses on whether a single decrement in the strategic importance of the misspecified choice is significant, whereas the latter test uses the less demanding criterion of performance differences between misspecification of the focal policy and that of the 15th policy.[14]

Under a hierarchical pattern of interactions, fitness improves markedly as the preset mismatch shifts from one involving 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 (three significant results of a positive difference and three significant results of a negative contrast), although the second test, contrasting the focal policy and the 15th policy, does provide

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[13] It does not make sense to explore a random specification of the misspecified policy because the analysis completely explores the impact of different policies being misspecified.

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

Table 3   Constraints of History

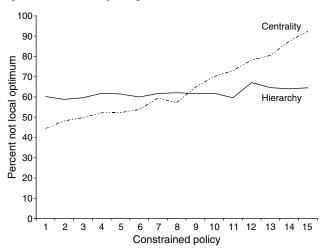| Policy misspecified	Hierarchy			Centrality		
	Final fitness	Difference (i vs. $i+1$)	Difference (i vs. 15)	Final fitness	Difference (i vs. $i+1$)	Difference (i vs. 15)
1	0.9308 (0.0447)	−0.0016**	−0.0148**	0.9377 (0.0425)	−0.0015**	0.0006
2	0.9324 (0.0447)	−0.0019**	−0.0133**	0.9392 (0.0414)	0.0003	0.0021**
3	0.9343 (0.0432)	0.0006	−0.0114**	0.9389 (0.0419)	0.0010*	0.0018**
4	0.9337 (0.0440)	−0.0034**	−0.0120**	0.9378 (0.0416)	−0.0007	0.0008
5	0.9370 (0.0421)	0.0014*	−0.0086**	0.9385 (0.0419)	0.0070	0.0014*
6	0.9356 (0.0429)	−0.0022**	−0.0100**	0.9378 (0.0421)	0.0070	0.0008
7	0.9379 (0.0418)	−0.0012*	−0.0078**	0.9371 (0.0423)	−0.0024**	0.0000
8	0.9390 (0.0414)	−0.0008	−0.0066**	0.9395 (0.0412)	0.0002	0.0024**
9	0.9398 (0.0411)	−0.0016**	−0.0058**	0.9392 (0.0415)	0.0012*	0.0022**
10	0.9414 (0.0400)	−0.0004	−0.0042**	0.9380 (0.0420)	−0.0001	0.0009
11	0.99418 (0.0395)	0.0002	−0.0038**	0.9381 (0.0416)	0.0009	0.0011*
12	0.9416 (0.0402)	−0.0020**	−0.0040**	0.9373 (0.0421)	−0.0023**	0.0002
13	0.99436 (0.0392)	−0.0014**	−0.0020**	0.9396 (0.0418)	0.0018**	0.0025**
14	0.9450 (0.0387)	−0.0006	−0.0006	0.9377 (0.0421)	0.0007	0.0007
15	0.9456 (0.0385)	0.0000	0.0000	0.9371 (0.0424)	0.0000	0.0000

*$p < 0.01$, **$p < 0.005$; standard deviations are provided in parentheses.

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 on other 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 2 that firms operating under the constraints of legacy misspecifications often fail to end up with 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 partic-

Figure 2   Final Policy Configurations

ularly evident in the case of the centrality interaction structure. Figure 2 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 of 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 a 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.[15]

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 percentages of local peaks in this analysis turn 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 pol-

[15] All of 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.

icy is misspecified.[16] Furthermore, although 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 depends 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 tends not to correspond to a local peak (i.e., a consistent set of policy choices). Rather, the firm in some sense accepts this misspecification.

4.3. Modes of Interaction: Influence, Dependency, and Autonomy

Table 3 and Figure 2 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). But our analysis of interaction structures up to this point somewhat conflates the role of influence and dependency in that policies that are relatively less dependent also tend to be less influential.[17] 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 6–10 as being influential with probability 0 and dependent with probability 1 (i.e., $r = 0$ and $p = 1$). The remaining five policies (policies 11–15) are treated as being autonomous (i.e., $p = 0$).

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[16] 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.

[17] Specifying the interaction structures solely by varying p^H and p^C would not eliminate such confounding effects. Variation in these parameters affects not only influence and dependency but also the level of autonomy or interdependence. Thus, the analysis in this section is an important supplement to the prior analysis but not a substitute.

Table 4   Extreme Adjacency Matrix

| Policy misspecified | Final fitness | Constraints of history | | | Fitness with partial activity map |
		Fitness − avg. influence	Fitness − avg. dependent	Fitness − avg. independent	
Influential					
1	0.9212 (0.0483)		−0.0150**	0.0019**	0.9590 (0.0454)
2	0.9216 (0.0480)		−0.0146**	0.0023**	0.9692 (0.0423)
3	0.9222 (0.0480)		−0.0141**	0.0029**	0.9802 (0.0367)
4	0.99214 (0.0483)		−0.0148**	0.0022**	0.9929 (0.0227)
5	0.99219 (0.0479)		−0.0144**	0.0026**	1.0000 (0.0000)
Dependent					
6	0.9368 (0.0439)	−0.0152**		0.0175**	1.0000 (0.0000)
7	0.9356 (0.0454)	−0.0139**		0.0163**	1.0000 (0.0000)
8	0.9365 (0.0440)	−0.0148**		0.0172**	1.0000 (0.0000)
9	0.9364 (0.0441)	−0.0147**		0.0171**	1.0000 (0.0000)
10	0.9359 (0.0446)	−0.0142**		0.0166**	1.0000 (0.0000)
Independent					
11	0.9194 (0.0510)	−0.0023**	−0.0169**		1.0000 (0.0000)
12	0.9193 (0.0509)	−0.0023**	−0.0169**		1.0000 (0.0000)
13	0.9196 (0.0612)	−0.0021**	−0.0167**		1.0000 (0.0000)
14	0.9196 (0.0633)	−0.0021**	−0.0167**		1.0000 (0.0000)
15	0.9186 (0.0645)	−0.0030**	−0.0176**		1.0000 (0.0000)

$^*p < 0.01$, $^{**}p < 0.005$; standard deviations are provided in parentheses.

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. Although 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, this 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 somewhat 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 noncontextualized choices, can readily be set at their 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 supported. 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. 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 and 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, most broadly, that it is useful to distinguish the degree to which choices are autonomous, influential, or dependent. Autonomous (or decomposable) choices are choices whose optimal resolution is independent of the firm's other choices and can therefore be made on the basis of standalone technical considerations. Highly influential choices are choices whose resolution impacts the optimal resolution of a great number of other choices and can be thought of as strategic: they are particularly important to get right. And finally dependent choices are tactical choices that can involve the mitigation of the effects of (misconceived) strategic choices as well as efforts to seek out incremental advantages. This very basic operational characterization is worth elaborating.

Autonomous choices disconnected from others are the ones for which the notion of universal best practices makes some sense. Note that although 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 independent of an overarching choice of strategy and therefore have the quality of operational policies (Porter 1996). And 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 (2004) and Rivkin and Siggelkow (2007) among others.

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. Our examination of examples suggested that 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 1a and 1b, 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 independent 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.

To conclude, strategic positions unfold over time. The impact of these temporal or diachronic linkages is importantly mediated by the presence of cross-sectional or synchronic linkages. The conjunction of the synchronic and the diachronic greatly increases the complexity of strategy formation. This paper has made a start at offering insights into their joint consequences.

6. Electronic Companion
An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

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