Changing Organizational Designs and Performance Frontiers

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Abstract

This paper empirically examines the relative performance and adaptiveness of generalist and specialist organizational designs in changing fitness landscapes over time. We apply Data Envelopment Analysis (DEA) to examine the organization design and performance of primary care medical clinics that serve a broad or narrow range of patient needs. DEA enables us to identify the frontier among generalist and specialist clinics. With longitudinal data, we construct a changing fitness landscape for these organizational units, and determine what proportions of changes in clinic performance are due to factors that are endogenous or exogenous to the clinics. We explore several micro and macro organizational design factors that may explain performance changes in clinics, and suggest directions for further research.

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Organization design; Performance, Adaptation; Frontier analysis
Introduction

Dr. Hal Patrick is president of a growing medical group of forty clinics located in local communities throughout this Midwestern state. He and his management team are working hard to design policies and procedures that will lower costs and increase quality of patient care across the group’s clinics. However, he is receiving complaints from physicians about the standardized rules and policies they view as unfair for evaluating their individual clinics. Some clinic physicians claim that the new organizational policies and contracts that were implemented uniformly across all clinics limit the flexibility of individual clinics to adapt to changing patient care needs in their local communities.

For example, Dr. Morgan, the lead physician of the Uptown internal medicine clinic admits that the new policies and contracts may decrease costs and improve quality of patient care over all the group’s clinics, but they decrease his clinic’s flexibility in serving unique and changing patient needs in his local community. He emphasizes that not all patients are alike--the same medical procedures cannot be delivered in the same way to all patients. His Uptown clinic has been serving a growing number of patients afflicted with AIDS, which complicates many standard medical care treatments. Dr. Morgan complains that the uniform reimbursement rate that the group negotiated for all clinics with a major health insurance payer does not adequately reimburse the Uptown clinic for the primary care it provides to AIDS patients. Instead, he says the contract favors providing medical care to healthy expectant parents being served by the group’s OB-GYN clinic located just 20 miles north of Uptown.

Dr. Patrick is seeking a response to these complaints. He asks, how can we design an integrated group practice that achieves low cost and high quality health care in all of our clinics, and
yet that recognizes that all health care is local and must be tailored to the unique needs of patients and communities that each clinic serves?

Dr. Patrick is not alone asking this question. It is a central question of designing headquarters-subsidiary relations in multi-business organizations that have many geographically dispersed units (such as manufacturing plants, service centers, and retail stores). Striking a balance between corporate-wide policies and subsidiary-specific factors is an enduring problem in macro and micro organization design (Dooms & van Oijen, 2008). On the one hand organization-wide policies and procedures are necessary in order to achieve economies of scale and create reliable and branded products from all of the organization’s stores, factories, or service centers regardless of their location. On the other hand, each dispersed unit requires some autonomy and flexibility in order to respond to its particularistic environmental task demands.

The literature on organization design (especially contingency and configuration theories) proposes that each organizational unit should be evaluated and designed to fit its differentiated local environmental demands and meet macro-organizational constraints (Drazin & Van de Ven, 1985; Meyer, Tsui & Hinings, 1993). However, specific methods and problems in diagnosing and implementing this proposition have received very little research attention. Not all dispersed units are organized the same way and face the same environmental task demands. These particularistic differences are often subtle and difficult to incorporate in organization-wide policies. As a result, macro-organizational policies that impose uniformities across dispersed units tend to advantage some units and disadvantage others in unknown and unintended ways. Because particularistic local contexts are difficult to assess and often change, they also tend to be overlooked in performance assessments of organizational units. This is especially so when it is difficult to attribute what aspects of observed changes in performance of organizational units are due to macro-organizational policies or unit-specific factors. As a result, the units benefiting from organization-wide policies
are unfairly rewarded for performance improvements that are not the result of their own efforts, while other units disadvantaged by uniform policies are disproportionately reprimanded for performance declines produced through no fault of their own.

To address these problems of balancing macro-organizational policies and micro-organizational autonomy, we build on complexity theories of organizing, and adopt a method of frontier analysis to empirically assess whether changes in the relative performance of different types of organizational units are attributable to the efforts of individual units or due to macro-organizational policies. To illustrate this, we present findings from a longitudinal study undertaken to empirically identify the relative performance of generalist and specialist organization designs from a sample of medical clinics studied from 1994 to 1999. We apply a method of frontier analysis to identify the relative efficiency of various organization units in terms of how well they maximize a set of performance output criteria subject to different combinations of inputs (local situations and patient needs). Longitudinal analysis shows adaptation processes on changing fitness landscapes, indicating how organizational units may increase, decrease, or sustain their relative performance over time. We also partition changes in performance of organizational units between endogenous and exogenous forces.

Conceptual Framework

Theories of Organization Design.

According to contingency and configuration theories, designing an organization represents a dual optimization problem: organizations are most effective when they maximize an external fit between environmental demands and design configuration, and an internal fit among its design components, such as strategy, structure, systems and culture (Meyer, Tsui & Hinings, 1993; Nadler & Tushman, 1999; Donaldson, 2001). Over the past decade, a literature on organizational
complexity has emerged that is useful for transforming this relatively static representation of the organization design problem into a more dynamic view of organizational adaptation and evolution (Anderson et al. 1999). The complexity perspective takes a more dynamic view of ‘fit’ by representing the relative height (external fit) and shape of the peak (internal fit) of work configurations as they evolve on a changing fitness landscape over time. Hill climbing reflects incremental changes in a configuration, while hill jumping represents radical and discontinuous changes from one design configuration to another on a rugged landscape.

The concept of fitness landscape was originally developed in evolutionary biology by Sewell Wright (1932), formalized by Kauffman (1993) and used to model organizational adaptation and change by Levinthal (1997), McKelvey (1999), Rivkin (2000) and Siggelkow (2001), among others. Siggelkow (2001) illustrates how notions of internal and external fit in contingency theory can be translated into fitness landscapes. He graphs the performance landscape of the Ford Motor Company’s low-variety/low-flexibility mass production system in the early 1900s (Figure 1a), and illustrates how its performance decreased in comparison with the Japanese (Toyota) high-variety/high-flexibility lean production system in the 1980s (Figure 1b).

-- Insert Siggelkow’s Figure 1 about here. --

Internal fit (i.e., the internal coherence of a particular design configuration) is represented by a peak in the landscape, and the steepness of the peak is a function of the interdependencies among components of the configuration. “Internal fit corresponds to a peak because changing any single element (and not changing any other element) within a consistent set of choices leads to a decline in performance” (Siggelkow 2001, p. 840). External fit – the performance of a particular design given environmental conditions - is represented by the height of a particular point on a fitness landscape. External fit encompasses all exogenous factors that affect the relative profitability of a particular
design configuration, including competitors’ actions, available technologies, and macro-
organizational policies.

Environmental changes during the 1900’s are represented by changes in the height, shape,
and location of peaks and the emergence of new peaks on the fitness landscapes in Figures 1a and
1b. For instance, given the production technologies available in the early 1900s, low-variety/low-
flexibility production systems were very efficient. However, the performance of this work system
configuration declined relative to the high-variety/high-flexibility production configuration that
became technologically feasible by the 1980s.

Kauffman (1993) modeled this concept of fitness landscapes with his “NK(C)” model,
where N is the number of elements in the system, K is the degree of interdependence among these
elements within the system, and C reflects the system’s coupling with other co-evolving systems in
the landscape. Levinthal and Warglien (1999, pp. 344-345) modeled alternative kinds of fitness
landscapes that emerge with variations in K and N. When K is low compared to N, the landscape
will tend to have a very large smooth basin of attraction leading to a single peak. Low
interdependence among system components in the fitness landscape implies a situation where one
can pursue universal best-practices. Each component actor improves the fitness of the overall
system by improving his or her own contribution to fitness. Single-peak landscapes with smooth
adaptation surfaces are robust designs. Levinthal and Warglien (1999, p. 347) point out that a
single peak fitness landscape “solves the problem of coordination, but it does so at the cost of
diversity.” Levinthal and Warlingen (1999) also modeled more complex dynamics produced by
coupled landscapes where the fitness of an actor shifts and deforms as the result of c, the adaptive
efforts over time of other interdependent actors at other levels. Coupled landscapes illustrate how
coevolving actors shift the landscape topography for each other.

In terms of our opening example, the actors are clinics who are engaged in climbing two
hills representing specialist and generalist kinds of organizational designs. As discussed in greater detail below, the specialist hill consists of clinics that serve patients with a particular kind of disease or need, while the generalist hill includes clinics that provide a broad array of healthcare services for a wide variety of patients. Hill climbing for the clinics is on a continually shifting landscape. Macro policy decisions at the group level (such as a reimbursement contract) seldom have uniform consequences at the micro level. Macro policies may shift the relative positions of clinics on their respective hill, just as it may increase or decrease the height of their hill in comparison with other coupled hills on this metaphorical landscape. The image of actors “dancing” across a fitness landscape over time is apropos, as actors adapt to each others’ steps as well as to moving frontiers. Through this process, some improve and others fall behind. Still other situations reflect “Red Queen” dynamics (Barnett and Sorensen 2002; Derfus, et al 2008), where competing actors invest great effort in fine tuning their fitness landscapes, but then find their relative positions have not changed or deteriorated over time.

These concepts of internal and external fit in the designs of organizations as being reflected in the shape and height of design hills on a metaphorical fitness landscape are attractive, abstract ideas. But ‘the devil is in the details’ when operationalizing and empirically observing these concepts. In particular, what organizational dimensions or variables are important for measuring internal and external fit? The literature tends to assume that all design variables must fit together both internally and externally (Donaldson, 2001). For example, configuration theory proposes that organizational structure, systems, culture, incentives, and strategies must all be internally coherent and fit environmental demands (Meyer, Tsui, & Hinings, 1993). Complementarity and complexity theories question this proposition by emphasizing the need to treat interdependent variables as a set (Whittington & Pettigrew, 2003; Siggelkow & Levinthal, 2003). What remains to be determined is which variables should be treated as interdependent sets for achieving internal and external fit?
Achieving both is difficult (Child, 1975; Khandwalla, 1973), and often forces making trade-offs between achieving internal and external fitness (Miller, 1993). This suggests that achieving internal and external fit is not likely to involve the same organizational factors because internally coherent organizational arrangements do not predict external fitness with environmental demands (Sinha & Van de Ven, 2005)

Specifying the details of these organizational configurations remains an elusive goal, particularly in situations with multiple conflicting environmental demands, internal design configuration tradeoffs, and diverse performance expectations. In these situations it becomes difficult, if not impossible, to specify in concrete terms the operational meanings and relationships among these abstract notions of organization environment, configuration, and performance. To move beyond the limits of arm-chair theorizing, we propose taking an empirical approach using methods of frontier analysis. This paper shows that these methods provide an empirical way to advance our understanding of the changing configurations of organization designs.

**Frontier Analysis.**

Empirical study of organizational fitness or adaptiveness involves two steps: (1) identify the most efficient organizations in a sample that best achieve performance outcomes subject to their particular resource and environmental constraints, and then (2) analyze their design configurations with those of less efficient comparable organizations facing similar resource and environmental constraints (Donaldson, 2001; Meyer, Tsui & Hinings, 1993). The first step entails a constrained-maximization problem of calculating the maximum performance outputs of organizational units in a sample subject to different resource and environmental input constraints. The second step treats this calculated result from step one as the dependent variable whose variance is explained in terms of a set of organizational design factors using a standard regression model.
To perform the first step of the analysis, we chose a method of frontier analysis in order to avoid a logical problem with regression-based models, as used in prior studies of configuration and complexity theories of organization design (e.g., Drazin & Van de Ven; 1985 and Doty, Glick & Huber, 1993). As Bryce, Engberg & Wholey (2000:511) discuss, regression is designed to explain variance in average behavior; for example, \( Y = f(X) \) estimates variations in average outputs, \( Y \), from a set of independent variables \( X \). In contrast, frontier analysis mathematically calculates the outlying ideal-type organization that maximizes desired performance outputs subject to its particular input constraints (Lewin & Minton, 1986). This latter estimate, at least intuitively, provides an appropriate measure of the relative efficiency of organizational units facing comparable constraints. Frontier analysis provides a more direct method of empirically identifying these most-adaptive outliers in a sample of organizations than regression methods that examine the distance of residuals from the center of a least squares line.

Frontier analysis is a method that focuses on the outliers in a sample. It empirically identifies the most adapted or best performing units on the outlying frontier in the sample, and then provides a way to examine the relative distance of other cases in the sample from their comparable cohorts on the frontier. Frontier analysis directly addresses the constrained optimization problem in contingency theory that is central to configuration and complexity perspectives (Sinha & Van de Ven, 2005). The best performance frontier consists of organizational units that maximize desired output criteria subject to input resource and environmental constraints in comparison with others examined in the sample. The results from frontier analysis can also be used to identify the peaks and plot the relative location of units on a fitness landscape to produce a graphic illustration as in Figure 1.

The particular form of frontier analysis that we used is Data Envelopment Analysis (DEA). DEA is a non-parametric frontier estimation method that was developed by Charnes, Cooper, and
Rhodes (1978). Charnes, Cooper, Lewin, and Seiford (1994) and Thanassoulis (2001) provide informative introductions to DEA. Instead of trying to fit a regression plane through the center of the data, DEA floats a piecewise linear surface to rest on top of the observations (i.e., DEA envelops the observations and, hence, the name Data Envelopment Analysis). Compared to other frontier estimation methods, the features of DEA that make it particularly appropriate for our research objective of studying organization designs are that (1) it can handle multiple input and output variables where each variable may be measured in different scales, (2) it does not require that functional relationships be specified between the input and output variables, and (3) it allows a non-linear shape to the frontier and thereby facilitates study of equifinality; i.e., equally-effective alternative organizational designs (Gresov & Drazin, 1997). We also show below how longitudinal observations of a sample of organizations can be analyzed with DEA to determine changes in performance frontiers over time, and the relative moves of organizational units onto and off of the shifting frontier over time.

Figure 2 provides a geometric intuition on how DEA works. DEA searches for the weights that optimize outcome performance measures (the Y axis) subject to a set of input factors (on the X axis) for organizational units being investigated. Once scores are calculated, a best performance frontier can be identified from which other units can be compared. A best performance frontier refers to the maximum output that can be attained given a set of input conditions for a sample of units that use a similar transformation process to convert inputs to outputs (Jayanthi, Kocha, and Sinha, 1996).

-- Insert DEA illustration in Figure 2 about here. --

Exemplary applications of DEA in organizational studies have been made by Lewin and Minton (1986), Chilingarian (1996), Cooper, Sinha and Sullivan (1996), and Johnson et al (1996).
DEA has also been used in several health care settings: to evaluate the efficiency of U.S health maintenance organizations from 1985-1994 (Wholey & Bryce, 1997), physician efficiency in hospitals (Chilingerian, 1996), primary health care in England (Salinas-Jimenez and Smith, 1996), primary care physicians of a large HMO in the Eastern U.S. (Chilingerian and Sherman, 1996), and case workers in home health care services (Johnson, et al., 1996). With the exception of the Wholey & Bryce (1997) study, all others used DEA to examine cross-sectional data.

It is important to note that our objective and method in using the DEA frontier analysis differs from these prior applications. Past studies have used DEA results as the final deterministic criterion to evaluate and prescribe interventions for the specific organizations being investigated. Our objective is less specific and more general. It is to draw inferences of study findings that go beyond the immediate sample in order to advance a more general theory of organization design. We also use DEA as a step one procedure to identify the organizational units on a best-performance frontier, which we treat in step two as a dependent variable to analyze and explain alternative organizational designs using a standard regression-based model.

Longitudinal data are needed to examine more dynamic issues of how organizational units adapt over time to change their relative positions on or off the best performance frontier, and how this frontier may change over time to produce Red Queen dynamics. Thanassoulis (2001) describes extensions and applications of DEA for examining whether productivity changes are due to the endogenous efforts of organizational units or exogenous shifts in the environment of the macro-organization. In terms of fitness landscapes illustrated in Figure 1, these changes in the performance frontier represent shifts in the relative fitness (i.e., the height and shape of hills) of alternative organization designs.
Methodological Steps in Frontier Analysis

We now apply these notions of frontier analysis and fitness landscapes to develop an empirical answer to Dr Patrick’s introductory question of how to design an integrated group practice that achieves low cost and high quality health care across all primary care clinics, and yet provides sufficient autonomy and flexibility for adapting to unique needs of patients and local communities? To address this question, we followed five steps in using the DEA method of frontier analysis (Sinha and Van de Ven 2005):

Step 1. Develop an empirical model of the key input, design, and output variables for measuring the organizational units in the study sample.

Step 2. Collect longitudinal data on the organizational units in terms of the variables in the model.

Step 3. Conduct frontier analysis using Data Envelopment Analysis (DEA) to identify the best performance frontier of organizational units in each year they are measured.

Step 4. Examine movements of organizational units on and off the best-performance frontier over time. Partition these performance differences into those attributable to factors endogenous to the units and those due to exogenous environmental or macro-organizational sources.

Step 5. Examine the organizational design configurations that may explain DEA performance variations that are due to endogenous clinic factors and macro-organizational policies or exogenous environmental factors.

Methods in performing each step are now discussed. Findings from these steps are presented in the next section. Our methods were informed by the literature on organization design and by medical group practitioners. As researchers we facilitated an unusual amount of engagement of medical group practice managers and physicians in making decisions and reviewing findings on each step of the frontier analysis. We felt their active involvement in each step was necessary in order to inform concrete applications of our methodology and to increase the likelihood that our research was relevant in addressing pragmatic managerial problems of clinic organization design. The observations and feedback of medical group practitioners are included in describing each step below.
Step 1: Develop empirical model of organizational units.

This research is part of a larger longitudinal study of organizational integration in a large Midwestern managed healthcare system. This system is a large vertically-integrated healthcare provider (with 20,000 employees and $2 billion revenues) that was created through a merger in 1994 of 15 hospitals, about 40 primary care clinics, a variety of homecare and ancillary services, and several health insurance plans that cover over one million people. From 1994 to 2002 our study tracked the development and integration of the system’s medical group practice, that grew to a total of 50 acquired primary care clinics throughout the Midwestern state. Some of the clinics were acquired for strategic reasons of providing geographical coverage of the regions served by its sister health plan, while others were acquired to provide primary care and patient referrals to Midwestern’s hospitals. Combined, the medical group was staffed by about 450 physicians and 3,000 employees in 1997.

Specifying an empirical model of key clinic inputs and performance outcomes is the first and perhaps most important step in the research process. Model misspecification results in selecting the wrong organizational units on and off the frontier, and irrelevant findings for theory and practice. To decrease this likelihood, we collaborated with managers and lead clinicians of the medical group practice to develop an empirical model. Between 1996 and 1999 we met regularly with medical group senior managers to develop an empirical model of clinic input, design and outcome variables that the managers used to evaluate clinic performance and that prior research found to influence organization design. Table 1 presents the model that the managers and researchers jointly developed to assess the performance of clinics of different size and that served broad (generalist) and focused (specialized) patient needs.

--- Insert model in Table 1 about here.---
**Clinic Input Conditions.** A variety of input measures were explored to identify the most meaningful indicators of the different environmental conditions or settings of the clinics. These measures included clinic size, geographical location, type of primary care clinic, patient health severity mix, and type of patient base or service needs. Through a variety of analyses and a series of review sessions with clinic managers and physicians, we selected clinic size and breadth of patients served by the clinics as the input factors in the model.

Organization size (number of employees) was selected as the major resource input factor because labor costs accounted for about 80 percent of annual clinic operating costs. In addition, studies over the years indicate that size is perhaps one of the best overall predictors of organization structure (Tosi & Patt, 1967; Kimberly, 1976; Cullen & Baker, 1984; Bluedorn, 1993; Camison-Zornoza et al, 2004).

With regard to a key indicator of environmental demand, clinic managers and physicians emphasized the importance of the mix of patients served by different clinics. They referred to an internal consultant’s report of the different demands on clinics that serve a broad versus narrow mix of patients. They characterized patients of broad or generalist clinics as “option seekers” (where 58% of all patients are shoppers, basing decisions on urgency, convenience, and cost). In contrast the more focused or specialist\(^1\) clinics served a narrower mix of patients who they referred to as “relationship seekers” (42% want long-term relationships). Medical group managers observed that smaller clinics often appear more efficient and effective, but that may be due to their serving a more homogeneous set of patients. Larger clinics that serve a greater proportion of option-seekers stayed open longer hours (resulting in higher overhead and staffing costs), provide urgent care and more diverse services, and deal with patients who are not easy to keep satisfied. With the assistance of

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\(^1\) When referring to clinics as specialist or generalist we only mean the narrow or broad variety of patients served by a clinic. We do not include other terms commonly associated with medical specialists, such as greater expertise, prestige, or revenue.
the group practice managers and physicians, we classified the primary care clinics in this sample into two groups based on whether they serve a broad or focused mix of patients.

These focused and broad patient mixes lead to Carroll’s (1985) resource partitioning question of whether to design individual clinics to serve a wide (generalist) or narrow (specialist) range of services for its population niche? Hannan & Freeman (1989), McKelvey (1982), and Aldrich (1999) point out that specialists frame their identity in a narrow domain and do well when environmental conditions are stable and favor this domain. In contrast, generalists adopt a wider and more heterogeneous domain, which allows them to adapt more successfully when environmental demands change and are highly uncertain. In his resource partitioning model, Carroll (1985) argued that generalist and specialist designs are interrelated and can coexist. In concentrated markets, competition among generalists to serve multiple market segments creates opportunities for specialists to carve out distinctive niches not adequately served by generalists. By partitioning their market niches, generalists and specialists compete with their own kind, and not between kind. In terms of our fitness landscape metaphor, generalists and specialists occupy different design hills, compete with one another to be the ‘king or queen of their hill,’ but seldom engage in hill jumping.

One reason for the lack of hill jumping is that switching between generalist and specialist clinic designs represents a major organizational change that is seldom made quickly and without macro-organizational policy intervention. All of the clinics in our sample were imprinted with their generalist or specialist designs before they were acquired by the medical group. The macro-policy decisions of medical group managers did not change the generalist-specialist designs of clinics, but as we will see, they differentially affected these clinics.
Clinic Outcome Performance. Medical group managers and physicians selected two composite measures of clinic performance: Patient care (as measured with a patient satisfaction survey and our survey measure of clinical quality care as judged by clinic healthcare providers), and business care (clinic productivity, measured as the number of standardized clinical services (RVUs) per provider, and clinic profitability, measured as net revenue per provider from organizational records). Group practice managers confirmed the relevance of these performance measures. They reported using these measures in their performance appraisals of clinics and physicians within the clinics.

Clinic Organization Design. The middle column of Table 1 shows the clinic organization design factors that are used to explain variations in clinic adaptation in steps 4 and 5 below. They include supportive leadership, openness to ideas, work discretion, work standardization and resource availability, which are often included in studies of job or work design (Hackman, 1977; Van de Ven and Ferry, 1980; Lawrence & Dyer, 1983). Employee integration and motivation were also chosen as key clinic design factors, and prior studies suggest they are importantly associated with work incentives, recognition, and distributive justice (Vroom, 1964; Hackman & Oldham, 1975; O’Reilly, Chatman & Caldwell, 1991; Kanfer, 1995; Mayer, Davis & Schoorman, 1995). These organizational and individual work design factors were defined, selected, and measured as follows.

1. Supportive Leadership. The immediate supervisor is typically the organization’s most immediate personification to the employee. The classic Ohio State leadership studies (e.g. Halpin & Winer, 1957; Stogdill, 1974) found that leadership behaviors emphasizing consideration (defined as relationship-oriented behaviors) and initiating structure (defined as task instrumental or work-related behavior) were strongly related to employee satisfaction and performance (for a review, see Behling & Schriesheim, 1976). Supportive leadership refers to behaviors of leaders that supports people in doing their work by providing constructive
feedback, building inter-personal relationships and encouraging work accomplishment. Five items from Van de Ven & Chu's (1989) index were used to measure supportive leadership (coefficient alpha = .81).

2. **Openness to Ideas.** Argyris (1977) proposed that powerful norms often prevent employees from saying what they know about technical and policy issues in organizations. Morrison and Milliken (2000) review studies showing the powerful influence of group norms in limiting individuals to express their beliefs and opinions about organizational issues. Openness to ideas is defined as the extent to which employees feel free to critique and challenge organizational actions, voice doubts, and feel diverse ideas are respected. We adapted four measures of openness to change and freedom to express doubts from Van de Ven and Chu (1989) index, and their coefficient alpha = .85.

3. **Work Discretion.** A core dimension of job and organization design (Hackman & Oldham, 1976; Van de Ven & Ferry, 1980) is work discretion, or autonomy. It is related to experienced responsibility for work outcomes, including high-quality work performance, job satisfaction, and decreased absenteeism and turnover (Hackman, 1977; Hackman & Oldham, 1976, 1980). Work discretion refers to the extent to which employees influence decisions about what work to perform, how work is performed, and developing work policies or procedures. Three items adapted from Van de Ven & Ferry's (1980) index were used to measure work discretion, and their coefficient alpha = .80.

4. **Work Standardization.** While organizational changes may require employees to adapt to unique tasks or exceptional routines, the value of standardized work procedures is that they can reduce hassles and increase efficient coordination of repetitive work activities. Coordination is often achieved through job descriptions, policies and procedures that specify individual roles and rules for performance. Goffman (1959) proposed that roles, like rules, smooth interaction in groups. Roles and rules help employees know what to do to meet others’ expectations and what they can expect from others. Work Standardization was measured with Van de Ven & Ferry’s three-item index of the extent to which work is clearly defined, that employees follow rules and procedures in the jobs, and the number of rules followed (coefficient alpha = .60).

5. **Resource Availability.** Lawrence and Dyer (1983) propose that innovation is maximized when a moderate level of resources are available. Too few resources force organizations into survival mode and stifle innovation; too abundant resources may provide too little stimulus to innovate.
Van de Ven and Chu (1989) found that availability of needed resources is positively related to innovation performance. Resource availability was measured with a single survey item of the extent to which respondents perceive that they lack the needed resources or adequate support in their work.

6. **Incentives.** Expectancy theories of motivation have shown that an employee will be motivated to exert effort toward achieving recognition, desired rewards from doing good work, and avoid sanctions from doing work poorly (Hackman & Oldham, 1975). The perceived likelihood of being rewarded for good work and sanctioned for poor work was measured with items from Van de Ven and Ferry (1980). Recognition was measured with a single question asking respondents how often they experienced recognition for their efforts.

7. **Fairness.** Homans (1961) introduced the concept of distributive justice, referring to the perceived fairness of reward distribution. Thibaut and Walker (1975) introduced a related concept, procedural justice, referring to the perceived fairness of policies and procedures used to allocate resources (both benefits and costs) among employees. Studies have found that perceptions of distributive justice are strongly related to job satisfaction and satisfaction with rewards. Procedural justice is also strongly related to organizational commitment, policy and procedure acceptance, and minimizing negative reactions to adverse outcomes such as layoffs or pay cuts (for a review, see Greenberg, 1990). Thus, employees are more likely to be willing to exert effort to implement organizational objectives if they perceive that limited resources are distributed fairly, that the organization treats employees fairly, and that the organization follows due process procedures. Fairness was measured with five survey items as the extent to which respondents perceive that the organization’s managers behave fairly, the organization’s programs and policies are fair, and employees are rewarded fairly for their efforts. Fairness was measured with five items developed by Wallace (1995) and Price & Mueller (1981) (coefficient alpha = .83).

**Step 2: Longitudinal Measurement**

Data on the clinic input, design, and outcome variables listed in Table 1 were collected in the Fall of 1997 and again in the Fall of 1999. In each wave the data came from three different sources. First, we were given access to patient satisfaction surveys that were conducted in 1997 of
7700 patients and in 1999 of 8,000 patients who were served by the primary care clinics. The group practice contracted with an independent healthcare survey organization to conduct the patient satisfaction surveys. After cleansing the data of any patient identification information, the vendor provided us a copy of the patient satisfaction surveys for each clinic. Second, data on clinic environmental characteristics and economic performance were obtained from organizational records. Third, as discussed in the previous step, we designed and conducted questionnaire surveys and obtained responses from about 1000 employees of all clinics in 1997 and 1999 that included measures of perceived quality of health care and other clinic organizational design characteristics.

The specific sample of organizational units examined in this study consists of 32 primary care clinics\(^2\) that are owned by the large managed care organization. Given the relatively small number of clinics for statistical analysis, we had to restrict the scope of the model by selecting the fewest number of clinic input and outcome variables.

**Step 3: Conduct the Frontier Analysis.**

As mentioned in the introduction, not all clinics are alike. Performance comparisons among primary care clinics may not be valid because some clinics address more difficult patients and other environmental task demands than do other clinics. In other words, some organizational units are “dealt a different deck of cards” than others. Given these input constraints, some units accomplish more with the “cards they have been dealt” than others. DEA provides a method to systematically identify and partition performance of organizational units facing these different kinds of input constraints along a best performance frontier.

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\(^2\) Due to missing data and combined organizational accounting statements for some clinics, some of the 40 clinics in our initial sample had to be removed for this analysis.
DEA was performed on the sample of clinics measured in 1997, and then again on data collected in 1999. Mathematically, DEA computes the efficiency of clinics (called decision-making units (DMU) in the DEA literature) with the following equation:

$$\text{Maximize } E_u = \frac{\sum_{i=1}^{n} y_{ru} \cdot O_{ru}}{\sum_{i=1}^{m} x_{ru} \cdot I_{ru}} \ldots \ldots (1)$$

where $u$ represents the units of DMU; $E$ represents performance efficiency; $I$ and $O$ represent respectively all inputs and outputs for each DMU; and $x$ and $y$ represent the weights assigned to each input and output. These weights are chosen in such a way that the DEA efficiency ratio is maximized for each DMU in the interval $[0, 1]$. As Figure 2 illustrates, this frontier bounds (“envelopes”) the remaining data points from above, and the interior observations of DMUs below the frontier receive non-negative scores less than 1 based on their proximity to the frontier. (Bryce, Engberg & Wholey, 2000: 513).

Following Thanassoulis (2001), we evaluated clinics’ efficiency in two steps. They enable us to separate between endogenous managerial and exogenous policy or environment effects on clinics’ performance. We adopted a non-parametric, deterministic, output-based, variable-returns-to-scale specification of the DEA model. This specification of the DEA model achieves our two-step objective of identifying the clinics that maximize multiple outcomes (patient and business care) with the least amount of resource inputs (clinic size). This computed DEA score is used in the first

3 There are of course alternative ways to compute unit efficiency. Bryce, Engberg & Wholey (2000) compare three commonly-used approaches: DEA (as described here), stochastic production frontier (Aigner, Lovell & Schmidt, 1977; Meeusen & van den Broeck, 1977), and fixed-effects regression (not used here for reasons discussed before). Based on data from 585 HMOs operating from 1985-1994, they find that the results from the three methods identify the same industry trends and that correlations of individual unit efficiency scores from the three methods vary from .67 to .79. While these results show high agreement, Bryce et al (2000) caution that the results are not identical because, indeed, the different methods are designed for different purposes.
Step 4: Endogenous and Exogenous sources of Clinic Productivity Changes

Best performance frontiers are not static; they change over time (Sinha 1996). This implies that the frontier is a moving target and that clinics move on and off the shifting frontier over time. Longitudinal analysis of the clinics in 1997 and 1999 permits analysis of these dynamic issues. Thanassoulis (2001) describes promising extensions and applications of DEA on longitudinal data for examining whether productivity changes over time are due to the endogenous managerial efforts of the organizational units being evaluated, or due to exogenous policy shifts in the environment or macro-organization. This involves the use of the Malmquist Index (Fare et al. 1994).

The Malmquist Index (MI) assesses productivity change by considering the efficiency of a DMU (in comparison with other DMUs) in two different time periods according to the following equation:

\[
M.I. = \sqrt[\text{Time2 - Time1}]{\frac{\text{Efficiency of DMU}_j \text{ at Time1 with respect to Time1}}{\text{Efficiency of DMU}_j \text{ at Time2 with respect to Time2}}} \times \frac{\text{Efficiency of DMU}_j \text{ at Time2 with respect to Time1}}{\text{Efficiency of DMU}_j \text{ at Time1 with respect to Time2}}
\]

This equation computes a geometric mean of the efficiency change of a particular DMU at two different time points. In the above formula, the two terms “Efficiency of DMU\(_j\) at Time\(_1\) with respect to Time\(_1\)” and “Efficiency of DMU\(_j\) at Time\(_2\) with respect to Time\(_2\)” are relatively straightforward. In our case, they are simply the DEA scores of a particular clinic in 1997 and 1999.\(^4\) The other two terms “Efficiency of DMU\(_j\) at Time\(_2\) with respect to Time\(_1\)” and “Efficiency of DMU\(_j\) at Time\(_1\) with respect to Time\(_2\)” are less intuitive. Both of them evaluate the efficiency of a focal clinic in one year with respect to all clinics (including the focal clinic itself) in another year.

\(^4\) However, because of the methodological requirements of Malmquist, we need to assume constant returns to scale here. This is different from our DEA Steps 1 and 2 above. But this change in assumption does not affect our analysis substantively.
An example of how the MI (Malmquist index) is computed for a specific case is useful here. Suppose we are interested in the productivity change of clinic C1 in our sample. According to the above equation, we conduct four DEA runs and obtain the following four measures regarding clinic C1’s efficiency:

- Efficiency at 1997 (Time 1) with respect to 1997 (Time 1): 28.50
- Efficiency at 1999 (Time 2) with respect to 1999 (Time 2): 13.50
- Efficiency at 1997 (Time 1) with respect to 1999 (Time 2): 25.10
- Efficiency at 1999 (Time 2) with respect to 1997 (Time 1): 15.10

MI for clinic C1 is therefore:

\[
M.I. for \text{ Clinic 1: } \sqrt{\frac{13.50}{28.50} \times \frac{25.10}{15.10}} = 0.53
\]

To facilitate interpretations, we subtract 1 from this number. Thus, total productivity change for clinic C1 is now -.47. The negative sign indicates that clinic C1 experienced a decline in total productivity between 1997 and 1999. We perform this simple transformation for all the clinics in our sample, and the values are presented in the last column of Table 6.

Fare et al. (1994) show that MI can be decomposed into two components (that which is attributable to the DMU’s endogenous efficiency change and that due to an exogenous frontier policy or environmental change). The first component is simply a ratio between Efficiency of DMU\(_j\) at Time\(_1\) and Time\(_2\):

\[
\frac{\text{Efficiency of DMU}_j \text{ at Time}_2 \text{ with respect to Time}_1}{\text{Efficiency of DMU}_j \text{ at Time}_1 \text{ with respect to Time}_2}\]

The second component has a form very similar to the MI index, but there is an important difference: the denominator of the first term and the numerator of the second term interchange:

\[
\left(\frac{\text{Efficiency of DMU}_j \text{ at Time}_2 \text{ with respect to Time}_1}{\text{Efficiency of DMU}_j \text{ at Time}_1 \text{ with respect to Time}_2}\right)^{1/2}
\]

The second component has a form very similar to the MI index, but there is an important difference: the denominator of the first term and the numerator of the second term interchange.
The Malmquist Index is equal to the multiplication between these terms: \( MI = \text{Efficiency Change} \times \text{Frontier Change} \). For example, in our case, efficiency change for Clinic 1 is \( \frac{13.50}{28.50} = 0.47 \). Frontier change is \( \sqrt{\frac{15.10}{13.50} \times \frac{28.50}{25.10}} = 1.13 \). That is, \( 0.53 = 0.47 \times 1.13 \). As mentioned, we subtract 1 from the original value. Thus, a positive MI value indicates an increase in productivity and a negative value indicates a decrease in productivity. The last three columns of Table 4 (discussed in the findings below) report the values of MI in terms of total productivity change, clinic’s efficiency change and frontier change for all clinics.

**Step 5. Organization Design Profiles of Adapting Clinics.**

In the last analysis step we examine the organizational design factors that may explain total productivity changes in clinics, in terms of endogenous clinic efficiency efforts and exogenous group frontier changes. Given the limitations of small sample size, we rely on simple correlation analysis to identify the clinic organizational design characteristics that are related to DEA effectiveness for the clinics in this sample.
Findings

We now report and discuss the empirical findings from each of the five steps in our analysis.

1. Clinic Performance Findings.

Table 2 shows the correlations among output measures of clinic business and patient care performance. Three findings are notable. They are presented here and linked with other findings in later sections. First, the measures of patient care satisfaction (participative provider care, staff courtesy) are highly correlated. This indicates that patients perceive a more satisfying care experience in clinics that provide a participative approach to doctor-patient relationships, where staff members treat patients with respect, and where clinic providers emphasize patient care quality as a goal.

— Insert Clinic Outcomes Correlation Matrix in Table 2 about here. —

Second, the two measures of business care (clinic productivity and profitability) are uncorrelated \((r=-.02)\). Increasing the productivity of providers was unrelated to increasing clinic profitability. Contrary to popular assumptions, the economic performance of the primary care clinics in this sample is not strongly influenced by increasing physician productivity. This finding surprised the group practice managers who at the time were encouraging their physicians to be more productive in order to reduce clinic financial losses. It led managers to question their superstitious learning behavior, which Schwab (2007) also observed among managers who do not let sufficient time pass before assessing the effects of prior actions. Finding no relationship between physician productivity and clinic income led managers to explore other plausible factors that may explain clinic profitability, including factors exogenous to the clinics, such as clinic acquisition strategy, group health plan contracting, facility capitalization, and cost accounting practices at the macro-organization level.
Third, Table 2 shows that measures of patient care are not correlated with measures of business care. For example, perceived patient care quality is not significantly correlated with net revenue per provider ($r=-.05$). This finding questions another instance of superstitious learning among clinic physicians who often expressed fear that clinic cost-cutting efforts were compromising patient care quality. These data indicate that clinic business care and patient care are independent. Advancing one outcome does not decrease or increase attaining the other desired outcome in this sample of clinics.

2. Clinic Input Findings.

Table 3 presents a comparison of the clinics serving broad (generalist) versus focused (specialist) mix of patients. The table shows that significant differences exist among the two groups of clinics on nearly all performance and clinic environmental conditions. In terms of input conditions, the specialist clinics typically serve a focused mix of patients, such as OB/GYN for expectant families, patients with diabetes and other chronic diseases, and more frequent and acute treatments of elderly patients. In addition to these kinds of patients, generalist clinics also serve a wider array of patients and families seeking less acute and chronic health care services, such as vaccinations, medical checkups, colds, flues, cuts, scrapes and drug prescriptions. Relative to generalist clinics, specialist clinics are smaller in size, have a greater proportion of internal medicine providers, and tend to be located closer to metropolitan centers (where there is greater industry concentration). Because they have medical conditions requiring long and repeated care, a greater proportion of patients in specialist clinics seek doctor-patient relationships, while more patients of generalist clinics seek immediate, competent, and comprehensive health care services when it is convenient for their busy work and family schedules. Site visits to some of clinics revealed that generalist (compared to specialist) clinics were not only larger but much busier with full waiting rooms and a constant buzz of clinicians and patients going in all directions. Given
these different patient expectations and practices, the findings in Table 3 are not surprising that patients served by specialist clinics are more satisfied with their care, perceive clinic staff as more courteous, and staff perceive they provide a higher quality of health care than generalist clinics.

Finally, the insignificant statistical differences between generalist and specialist clinics on business care appears due to the much greater variation in business care among specialized (focused) clinics than among broad generalist (broad) clinics.

When reporting these findings, managers of the clinic group practice stated that they had an intuitive appreciation of these differences between generalist and specialist clinics. However, they stated they had not explicitly incorporated these performance differences in their assessments of generalist and specialist clinics. Based on these findings they undertook further study of the performance differences between specialist and generalist clinics. Based on data from their health plan they found that the per-member per-month cost of the average patient served in the generalist clinics was $153, while it was $98 in the focused clinics.

-- Insert ANOVA of Broad and Focused Clinics in Table 3 about here. --

3. DEA Analyses Results

Following Thanassoulis (2001), we evaluated clinics’ efficiency in two DEA steps. The results of these two steps, repeated in 1997 and 1999, are reported in the columns, labeled “DEA-Step 1” and “DEA-Step 2” in Table 4. Step 1 evaluates each clinic’s efficiency in comparison with clinics serving the same type of patient mix (i.e., either generalist or specialist types), while Step 2 reports each clinic’s efficiency in comparison with all types of clinics in the sample. In terms of our fitness landscape metaphor, the DEA-Step 1 compares the relative performance among clinics located on their own design hill, while DEA-Step 2 compares the relative performance among clinics located on all (both generalist and specialist) hills.
As the DEA Step 1 columns show for 1997 and 1999, each design group has its own best-performing clinics. Clinics with DEA efficiency ratings of 100 in Tables 4 are on the best performance frontier for this sample, while the DEA scores of clinics with DEA effectiveness ratings lower than 100 indicate how far the clinics are off the frontier (relative to their best-performing peers). In 1997 clinics C23, C24 and C31 were on the frontier among broad clinics; whereas C17, C32, C41 and C57 were on the frontier among focused clinics in that year. In 1999 clinics C14 and C31 were on the frontier among broad clinics; whereas C17, C32, C42 and C60 were on the frontier among focused clinics in that year. Only clinic C31 among broad patient care clinics, and clinics C17 and C32 remained on the frontier in both years, while other clinics came on and fell off the frontier relative to their cohorts.

The relative performance efficiency of clinics operating under different policy types in each year is indicated in the DEA Step 2 columns of Tables 4. The Table shows that specialist clinics designed to serve a focused patient base have higher DEA efficiency scores than do generalist clinics serving a broad patient base. In fact, not one generalist clinic has a DEA efficiency score that exceeds the lowest-performing specialist clinic in 1997 and 1999.

Figure 3 illustrates these findings by plotting the clinics on their DEA-Step 2 scores in 1997 and 1999. As the figure shows, there are dramatic DEA performance differences between generalist and specialist clinics in both 1997 and 1999. Equally clear from the figure is the close clustering among generalist clinics in the low DEA efficiency range, and the even closer clustering among specialist clinics in the high performance range in 1997 and 1999. The correlation between 1997 and 1999 DEA efficiency for all clinics is .97 (statistically significant), while it is only .33 among
clinics within each design type. As these data suggest, the specialist and generalist types of clinics are located on different organization design hills of our metaphorical fitness landscape, with the specialist design hill much higher in fitness than the generalist design hills.

It is noteworthy that between 1997 and 1999 no clinic changed between its specialist and generalist type of design structure. That is, when we analyze the relative efficiency of all clinics together, adaptation was limited to small variations among clinics of the same type. This indicates that between 1997 and 1999 the clinics in this sample engaged in local adaptation and fine-tuning among clinics on their design hill, rather than jumping between hills.

In summary, these findings show that the performance landscape of specialist clinics was higher than that of the generalist clinics. Between 1997 and 1999 some generalist clinics significantly improved their DEA performance relative to other clinics on their design hill, but none were able to catch up to the superior performance of specialist clinics. In terms of Red Queen competitive dynamics (Barnett and Sorenson 2002; Derfus, et al 2008), the clinic managers may have “run as fast as they could and then find their performance relatively unchanged.” This may be a result of the other runners that managers have chosen in their race, or it may be due to exogenous policy or environmental reasons that are beyond immediate control of clinic managers. In either case, performance comparisons are limited to small variations among cohorts on the same hill, whereas hill jumping is necessary for making dramatic performance improvements (Levinthal & Warglien 1999; Siggelkow 2001). These findings are consistent with Carroll’s (1985) resource partitioning model discussed before.

To identify which organizational design factors may account for performance variations, we correlated the clinic organization design variables with clinic DEA efficiency measured in 1997.
Results are shown in Table 5. As already shown in Figure 3, the major macro policy variable, specialist/generalist clinic patient mix, is significantly correlated with DEA performance across all types of clinics. The other organizational and individual work design variables have very low correlations with DEA efficiency across all types of clinics. Within each type, however, most of these organization design variables are strongly correlated in expected directions with clinic DEA performance. Endogenous clinic DEA efficiency is significantly correlated with increases in supportive leadership, openness to ideas, likelihood of rewards, and decreases in perceived lack of resources and recognition. These design factors are all within the control of individual clinic managers. As expected they are all strongly associated with DEA efficiency endogenous to each type of clinic. However none of these clinic design variables has any effect on DEA efficiency between types of clinics. This is because designing generalist or specialist types of clinics is a macro policy decision that is beyond individual clinic control in the short run.

--Insert Table 5 about here--

4. Clinic Productivity Changes

The last three columns of Table 4 report the values of the Malmquist Index in terms of each clinic’s total productivity change from 1997 to 1999 that is attributable to the clinic’s endogenous efficiency change and its exogenous frontier change for all clinics. The correlation between endogenous efficiency change and exogenous frontier change is -.14, statistically insignificant. This indicates that local adaptation with cohorts on a given design hill does not increase the likelihood of adaptation to other hills on a fitness landscape of alternative organizational designs.

The right columns of Table 4 display clinic’s efficiency change, frontier change and total productivity changes from 1997 to 1999. These findings are easier seen with the 3-dimensional

---

5 Similar results in all substantive respects were obtained in correlations between 1999 clinic design and DEA performance measures.
graph in Figure 4. This figure reveals the generalist and the specialist landscapes graphically. The figure shows that the variance of changes in clinic's efficiency is quite similar between specialist and generalist clinics. With respect to group frontier changes, however, there is less variance among specialist clinics than among generalist clinics. These results provide evidence that specialist clinics occupy a narrower niche than generalists do—an observation that is consistent with the fitness of generalist and specialist organizations to course- or fine-grained environmental niches (Hannan & Freeman 1977; Carroll, 1985). Moreover, specialist clinics uniformly benefit much more from exogenous group frontier changes than do their generalist counterparts. In terms of total productivity change, the variance among specialists is higher than that of the generalists.

---Insert Figures 4 about here---

The peaks and troughs in the changing performance landscape of the clinics in Figure 4 not only illustrate the performance consequences of changing organizational designs, but it also suggests that the transition from one design to another may be risky. Organization design literature has largely ignored the risks associated with changing organizations. Perhaps this is because most organization design studies are done with cross-sectional snapshots that do not provide information about the changing performance consequences of alternative organizational designs. Changes in the size and locations of performance peaks and troughs of clinics in Figure 4 call attention to such risks. In our case, the organizational design of specialist clinics reaches a higher performance peak, but also has a deeper trough than that of the generalist clinics. In other words, the specialist organizational design that had the greatest total productivity gains also had the highest total productivity losses over the same time period and in the same sample. This finding calls for an examination of the risk-return tradeoff of changing organizations, where higher returns are associated with higher risks, and lower returns are bounded with smaller losses and hence lower risk.
The only organizational literature that begins to touch on this risk-return tradeoff is complementarity theory, which suggests that during organization change performance may reflect a J-curve relationship over time. This is when the organization’s performance declines steeply for several periods and then improves slowly with time (Milgrom & Roberts 1995; Whittington & Pettigrew 2003). The peaks and troughs in Figure 4 suggest that the J-curve relationship may be possible if clinics change from the generalist to the specialist type. However, as noted before, no shifts between generalist and specialist clinic designs were observed over time in this sample.

5. Findings on Clinic Design

The last set of findings examine the organizational design factors that may explain total productivity changes in clinics, in terms of endogenous clinic efficiency efforts and exogenous group frontier changes. Given the limitations of small sample size, we rely on simple correlation analysis to examine how measures of organizational and individual work design are related to these DEA measures of changes in clinic efficiency, group frontier are total productivity changes. The results are shown in Table 6. Given the small sample size (n=32 clinics), the correlations are not statistically significant. However, the relative magnitudes and directions of the correlations reveal an important pattern. As Table 6 shows, almost all of the correlations between clinic design and total performance change wash out because the correlations of clinic design with clinic efficiency and with frontier (group) changes are in opposite directions.

These results remind us of the principle of opposite part-whole relationships (Simmel, 1955; Dahrendorf, 1979; Astley & Van de Ven, 1983). Many organization design problems and relationships manifest themselves in different and contradictory ways at different organizational levels. At the micro level the focus is on the particularistic needs of patients served by local
community clinics and on supportive organizational arrangements and individual motivators that enable this to happen. The same set of organizational and individual factors does not necessarily advance macro group level objectives, where the focus is on strategic policies, structural arrangements, standardized procedures, and incentives, supportive leadership and building co-worker trust for coordinating and controlling the delivery of health care in cost effective and high quality ways. Moreover, the substantive effects of clinic design factors can be different for different clinics, depending on their structure, patient-mix and fitness landscape.

**Conclusion**

Designing work across different levels of a complex organization, to date, has proven to surpass our mental capabilities in distinguishing performance outcomes of organizational units facing different environmental task demands and macro-organizational policies. To deal with these challenges, we proposed and illustrated an empirical method for assessing the designs of a sample of clinics that are part of one large medical group practice. Fundamental to this approach is conducting frontier analysis to define best performers using Data Envelopment Analysis (DEA), identifying clinics that are on and off the best practice performance frontier, and then comparing the work design profiles of the organizational units on and off their frontiers. We also illustrated how longitudinal study of a sample of organizational units permits systematic analysis of dynamic patterns of adaptation on changing organizational performance landscapes.

This paper has shown that an empirical approach to study configuration and complexity theories of organization design using methods of frontier analysis is doable and has promise. Unfortunately, our small sample of 32 clinics limited abilities to systematically examine the organizational design configurations of clinics moving on and off the frontier over time. But this research was not undertaken to test any theory; instead its purpose was to illustrate an empirical
approach for studying organization design. We think the methods and findings generate an important agenda of issues that require careful research attention to advance our knowledge of organization design, but which have been largely overlooked in previous research. They include the following five issues.

First, scholars and practitioners tend to be “mono-level” in attributing unit, group, or industry performance to the same level of organization being assessed. The DEA findings presented above clearly show that endogenous clinic-level factors as well as exogenous group-level frontier factors influence various performance criteria in different and unexpected ways. Three unexpected findings, in particular, called into question three organizational myths: (1) Does physician productivity influence clinic income? (2) Does clinic net income hinder patient care satisfaction or quality? (3) Do macro policy decisions at the group level have the same intended effects on organizational subunits? We presented empirical evidence for answering no to each question. In doing so this research identifies several instances of superstitious learning that many practitioners and academics have taken for granted or have not questioned.

Second, our study found that clinics with a specialist design were significantly more efficient than those with a generalist design. Given this information, why did managers at clinic and group levels not change the clinics from generalist to specialist designs? We speculate that Carroll’s (1985) resource partitioning model may provide a logical explanation. Carroll’s argument suggests that generalist and specialist designs are interrelated and can coexist. In concentrated markets (as present in the region of the healthcare clinics), generalist and specialist clinics partition their market niches, and compete only with their own kind, and not between kind. In terms of our fitness landscape metaphor, generalists and specialists occupy different design hills, compete with one another to be the ‘king or queen of their hill,’ but do not engage in hill jumping. The latter represents a major organizational change that requires macro-organizational policy intervention.
All of the clinics in our sample were imprinted with their generalist or specialist designs before they were acquired by the medical group. The macro-policy decisions of medical group managers did not change the generalist-specialist designs of clinics, but they differentially affected these clinics.

Third, factors at different organizational levels influence the performance of unit designs in different ways. In this study, clinics with a generalist design made productivity improvements only through endogenous means within their control. They gained no performance benefits from macro policy frontier changes over time. By contrast, specialist clinics gained significant productivity benefits from both exogenous frontier and endogenous clinic changes.

Fourth, graphing the changes in clinic performance provides heuristic insights on dynamic patterns in changing organizational landscapes. For example, from Figure 4 we drew the inference that some organization designs are more risky than others on a changing performance landscape. Although the literature on organization design has been silent about the risks involved in changing organizations, the size and locations of performance peaks and troughs in Figure 4 call attention to such risks. The organizational designs with the highest performance peaks also have the lowest performance declines.

Fifth, we illustrated a constructive way in which researchers can engage practicing managers in organizational research. Dr Patrick and his senior management team participated in decisions and discussions that informed each step of the research. As noted, the participative research process generated new and practical insights for managers about their organization. In response to our opening question, Dr. Hal Patrick stated that his management team is learning how to become more discriminating and identify “frontier clinics” in each policy group. Knowing which clinics are under-performing, he can also provide more informed suggestions for improving both medical group integration efforts as well as efficiency of individual clinics.
The major limitation of the findings presented here is that they are limited to, and cannot be
generalized beyond, the sample of organizational units observed. However, we believe that limited
generality of research findings is a necessary tradeoff for developing a more penetrating
understanding of organization design in real-world settings. As other studies in different contexts
accumulate, meta-analysis projects will provide opportunities to examine the generality of research
findings across samples and contexts.

While the findings cannot be generalized, we believe that the methodological approach
illustrated here represents a useful way to develop empirically-based models of organization design
and change. When applied to longitudinal research data, the approach addresses the criticisms that
contingency and configuration theories of organization design have been too static and only
applicable to simple and stable jobs and organizations. Our five steps in frontier analysis are also
intended to be managerially actionable, thereby addressing a common criticism of earlier work
design studies that they have not provided practical or concrete suggestions to managers for
improving organizational performance.
REFERENCES


Figure 1. Performance Landscapes

2a. Performance Landscape, Early 1900s

The Ford Production System (low flexibility, low variety) provides high performance.

2b. Performance Landscape, 1980s

The Japanese Production System (high flexibility, high variety) provides better performance, while the value of the Ford production system has decreased.

Figure 2. Geometric portrayal of a frontier using a single input – single output example

![Diagram showing a frontier with labeled points P1, P2, P3, P4, P5 with coordinates (x1,y1), (x2,y2), (x3,y3), (x4,y4), (x5,y5) and corresponding Y and X axes for inputs and outputs.]
Figure 3. Scatter-Plot of 1997 - 1999 Clinic DEA Efficiency
Figure 4. 1997-1999 Change in Clinic Efficiency Group Frontier and Total Productivity.
Table 1. Model for Clinic Frontier Analysis.

<table>
<thead>
<tr>
<th>Input Conditions</th>
<th>Medical Clinic Design</th>
<th>Performance Outcomes</th>
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<tbody>
<tr>
<td>Clinic Size</td>
<td></td>
<td></td>
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<tr>
<td>clinic total FTEs</td>
<td><strong>Work Design</strong></td>
<td><strong>Business Care:</strong></td>
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<tr>
<td></td>
<td>Supportive Leadership</td>
<td>Clinic Productivity</td>
</tr>
<tr>
<td></td>
<td>Openness to Ideas</td>
<td>(RVUs/Provider)</td>
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<tr>
<td></td>
<td>Work Discretion</td>
<td>Clinic Profitability</td>
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<td></td>
<td>Work Standardization</td>
<td>(Net Income/Provider)</td>
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<td></td>
<td>Resources Availability</td>
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<tr>
<td>Patient Mix</td>
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<td><strong>Patient Care:</strong></td>
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<tr>
<td>focused - broad</td>
<td><strong>Employee Integration</strong></td>
<td>Patient Satisfaction</td>
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<tr>
<td>mix</td>
<td>Incentives: Rewards/Recognition</td>
<td>Perceived Care Quality</td>
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<td></td>
<td>Fairness (distributive justice)</td>
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Table 2. Correlations among selected clinic outcome measures.

Table 2. CORRELATIONS AMONG SELECTED CLINIC OUTCOME MEASURES

<table>
<thead>
<tr>
<th>Patient Care Measures</th>
<th>Business Care Measures</th>
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<td>Participatory Care</td>
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<td>Staff Courtesy</td>
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<td>Anticipatory Care</td>
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Shaded cells are statistically significant correlations at .05 (2-tailed)
Table 3. ANOVA Comparison of Broad (Generalist) and Focused (Specialist) Clinics

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<th>Clinic Input Conditions</th>
<th>Clinic Performance Outcomes</th>
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<td>Patient Care Composite</td>
<td>RVU per Provider</td>
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<tr>
<td></td>
<td>ClinicType (1=FP, 2=Spec, 3=IM)</td>
<td>Patient satisfaction with care</td>
<td>Net Income per Provider</td>
</tr>
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<td>Distance from Metro Center</td>
<td>Patient perceived staff courtesy</td>
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<tr>
<td></td>
<td></td>
<td>Provider view of healthcare quality</td>
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<tr>
<td></td>
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Table 4. 1997-1999 Frontier Analysis of Clinics.

<table>
<thead>
<tr>
<th>Clinic ID</th>
<th>Macro Policy Type</th>
<th>1997 DEA</th>
<th>1999 DEA</th>
<th>Malmquist Index</th>
<th>Total Productivity Change (T)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Within-Type (Step 1)</td>
<td>Between-Types (Step 2)</td>
<td>Within-Type (Step 1)</td>
<td>Between-Types (Step 2)</td>
<td>Clinic Change (C)</td>
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<td>C16</td>
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</tr>
<tr>
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</tr>
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<td>74.49</td>
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</tr>
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<td>76.41</td>
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</tr>
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<td>Focused</td>
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<td>100.00</td>
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<td>99.00</td>
</tr>
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</tr>
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<td>100.00</td>
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<td>100.00</td>
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<td>98.70</td>
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<td>98.30</td>
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<td>99.00</td>
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<td>83.44</td>
<td>99.58</td>
</tr>
</tbody>
</table>

*Clinics sorted by Total Productivity Change (in descending order) and Type
*All values in three columns have been subtracted by 1. A positive value means an increase in efficiency and a negative value means a decrease in efficiency; a value of 0 means no change.
Table 5. Correlations between 1997 Clinic Design Factors and 1997 DEA efficiency scores.

<table>
<thead>
<tr>
<th></th>
<th>Endogenous Within-Type Clinic DEA efficiency</th>
<th>Exogenous Between-Types Clinic DEA efficiency</th>
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<tbody>
<tr>
<td><strong>Organizational Factors</strong></td>
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<td></td>
</tr>
<tr>
<td>Clinic type (0=specialist, 1=generalist)</td>
<td>.17</td>
<td>-.97**</td>
</tr>
<tr>
<td>Supportive Leadership</td>
<td>.46**</td>
<td>.10</td>
</tr>
<tr>
<td>Openness to Ideas</td>
<td>.40*</td>
<td>.00</td>
</tr>
<tr>
<td>Work Discretion</td>
<td>.34</td>
<td>.03</td>
</tr>
<tr>
<td>Work Standardization</td>
<td>-.00</td>
<td>.03</td>
</tr>
<tr>
<td>Lack of Resources</td>
<td>-.42*</td>
<td>.08</td>
</tr>
<tr>
<td><strong>Individual Factors</strong></td>
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<td></td>
</tr>
<tr>
<td>Likelihood of Rewards</td>
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<td>.17</td>
</tr>
<tr>
<td>Lack of Recognition</td>
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<td>.05</td>
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<tr>
<td>Fairness</td>
<td>.34</td>
<td>.11</td>
</tr>
</tbody>
</table>

N=32   * Correlation is significant at the 0.05 level (2-tailed); ** Correlation is significant at the 0.01 level (2-tailed).
Table 6. Correlations of 1997 Design factors with 1997-1999 Clinic, Frontier and Total Efficiency Changes

<table>
<thead>
<tr>
<th></th>
<th>Clinic Efficiency Change</th>
<th>Frontier Change</th>
<th>Total Productivity Change</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Organizational Factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clinic design (0=focused, 1=broad)</td>
<td>.19</td>
<td>-.89**</td>
<td>.07</td>
</tr>
<tr>
<td>Supportive Leadership</td>
<td>-.18</td>
<td>.13</td>
<td>-.17</td>
</tr>
<tr>
<td>Openness to Ideas</td>
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<td>-.14</td>
</tr>
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<tr>
<td>Work Standardization</td>
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<td>.068</td>
<td>.19</td>
</tr>
<tr>
<td>Lack of Resources</td>
<td>.22</td>
<td>-.07</td>
<td>.21</td>
</tr>
<tr>
<td><strong>Individual Factors</strong></td>
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<tr>
<td>Likelihood of Rewards</td>
<td>-.16</td>
<td>.15</td>
<td>-.15</td>
</tr>
<tr>
<td>Lack of Recognition</td>
<td>.27</td>
<td>-.07</td>
<td>.27</td>
</tr>
<tr>
<td>Fairness</td>
<td>-.09</td>
<td>.19</td>
<td>-.07</td>
</tr>
</tbody>
</table>

N=32
** Correlation is significant at the 0.01 level (2-tailed).