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INTERNAL STRUCTURES OF THE HEALTH MAINTENANCE ORGANIZATION AND THE QUALITY OF CARE

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This study investigates effects of HMO structural arrangements on performance, especially quality of care. The commonly used HMO types is assumed not effective in explaining performance differences. For the empirical test, I use bootstrap regression analyses with 36 HMOs. The results of the analyse show that decision-making participation and differentiation accompanied by coordination improve quality of care while formalization has a nonessential effect on quality of care. However, formalization and decision-making participation positively contribute to achieving coordination. The theoretical framework derived from the rational-contingency model of the formal organization better explains performance difference of HMOs than HMO types

INTRODUCTION

By 1970, the cost of increased indigent and elderly American health care access seriously concerned policy makers. Many attributed rising health care costs to Medicare and Medicaid or to scientific advances. But, a more fundamental explanation lay in the basic incentives in health care, especially financing arrangements (Williams and Torrens 1984; Starr 1982; Wolinsky and Marder 1985). As third parties, both private insurers and government programs effectively insulate patients and providers from the true cost of treatment decisions and so reduce the incentive to carefully weigh costs against benefits. With Fee-for-service (FFS), doctors and hospitals make more money the more services they provide, which encourages them to maximize service volume. Third-party, fee-for-service payment was the central mechanism of medical inflation. The rapid rise of prices and expenditures for personal health services during the early 1970s stimulated interest in HMOs. In other words, incentives to enhance earnings by prudent use of costly services theoretically replaced incentives to increase earnings by maximizing services. Slow economic growth and persistent inflation in the 1970s also undoubtedly aroused interest in HMOs to contain medical costs.

Three basic HMO types exist, although each type comprises considerable variation: Group Models, Staff Models, and Independent Practice Associations (IPAs). However, to distinguish basic HMO types in actual situations has grown more difficult. Important organizational variables make

HMOs, in some ways, as different as there are alike.

Researchers who use the basic types and ignore organizational diversity risk oversimplifying and misrepresenting the effects of HMO structures on performance. Much research tries to show that HMOs provide more cost efficient medical services than do conventional plans. Such research represents an effort to legitimatize the status of HMOs as health care delivery system. However, the studies lack a systematic approach for building cumulative knowledge about HMO performance. They do not consider a major finding in the organizational field, which is that structural arrangements of organizations are primary predictors of performance. They neglect, in other words, the systematic theoretical perspective and systematic knowledge accumulation that organizational theories proffer for assessing HMO structures arrangements and performance at the organizational level.

The basic research questions are probed:

1. Do HMO organizational structures have impacts on HMO performance?
2. If HMO structures have significant impacts on performance, what kinds of causal relationships exist?

THEORETICAL REVIEW OF FORMAL ORGANIZATION

Health care organizations on the whole are not yet well-represented in the body of research on complex organizations, and HMOs even less so. Health care organizational theorists contend that health care is a unique organization type (Shortell and Kaluzny 1983). However, the growth and diversity of prepaid health plans, HMO characteristics, and changes in environments proffer fertile research soil for organizational theorists.

Lawrence and Lorsh (1967), who coined the label "contingency theory", stress that organizations confront varying environments with differing demands and that organizations are in the interests of their effectiveness at the same time. Also, Thompson (1967) was among the first organization theorists to recognize the importance of the environment for organization structure and performance. In general, their work suggests that a more bureaucratic or "mechanistic" organization is more effective when the environments is simple and stable, tasks and technology are routine, and the percentage of nonprofessional employees are relatively high. Conversely, the less bureaucratic, more "organic" form of organization operates better when the environment is complex and dynamic, tasks and technology are not routine, and the percentage of professionals relatively high. The rational-contingency theory provides the main theoretical ground of this study.

Task Complexity of Health Maintenance Organization

I employ Perrow's approach (1967) to task complexity, an approach based on the raw material the organization manipulates. The nature of the raw material affects organization structure and operation. According to Perrow, the critical factors in the nature of the raw material, and hence of the task performed, are the number of exceptional cases it presents and the nature of the search process it requires when exceptional cases occur. Few exceptional cases arise when the raw material is objects that do not vary in consistency or malleability over time. Many exceptions obviously are found with human beings and their interactions, and hence in hospital or university population. Search processes range form those that are logical and analytical to those that must rely upon intuition inspiration, chance, or some other unstandardized procedure. Examples of the first form of search are the engineering process in many industries and most instances in computer programming. The second form of search arises in treating different medical patients and depends on professionals who seek information and provide advice. This form of task is found in work with humans, as in HMOs.

Dimensions of Structure

I give primary attention to four structural variables: (1) differentiation, or division of labor among participants and subgroups; (2) coordination; (3) formalization; and (4) centralization (participation in decision-making).

HMOs, as complex organization, mus differentiate structures for performing basic activities. The analysis of differentiation in complex. Its centrality in describing organizations can be traced to the earliest essays on the organization of work (see Gulick 1937; Weber 1947). Differentiation is an organizational response to work complexity (Lawrence and Lorsch 1967). In other words, task complexity necessitates differentiation in organizational characteristics for organizational effectiveness.

Once the activities of the organization have been differentiated, they must then be coordinated. A paramount and most difficult problem faced by all complex organizations in internal coordination—how best to gear resources and facilities together to attain organization objectives most effectively. Structural arrangements for coordination are contingent upon the situation being faced. Therefore, in situations of high uncertainty, better coordination achieves greater effectivness (Gerogopoulos and Mann 1962; Shortell, Becker and Neuhauser 1976).

Lawrence and Lorsch (1967) argue that the dimensions of differentiation and coordination are not separated but are connected elements.

Organizations that perform highly complex tasks require structural differentiation to be effective. Moreover, extensive differentiation requires greater coordination. Contingency theory implies an interaction effect between differentiation and coordination on performance.

In many ways, formalization is the key structural variable for the individual in an organization because its degree vitally affects a person's behavior. The amount of individual discretion inversely relates to the amount of behavior prepogrammed by the organization—the degree of formalization. In his review of the organization theory literature, Hickson (1966) finds no consensus among those writers as to the effect of rules and regulations (specified procedures or job specificity) on organzational or individual performance. A number of studies attempting to resolve this problem are summarized in rational-contingency theory. Lawrence and Lorsch(1867) hypothesize and provide evidence to support that unspecified procedures are more efficient in unstable, unpredictable, and diverse task environment. In short, the efficiency of formalization depends on organizational task complexity (Aiken and Hage 1968; Hage and Aiken 1969).

Some writers (Morse, Gordon and Moch 1974; Zeitz 1980; Flood and Scott 1987) suggest that centralization of decision-making negatively affects organizational performance under complicated tasks. Structural looseness such as low centralization (Thompson 1967) and lack of specificity such as low formalization (Gordon, Edward and Reich 1982) promote opportunity for the circulation of ideas and information, creative dialectics, and exercise of judgement and knowledge implied by the complexity or diversity of tasks.

Performance

This study use Etzioni's (1964) definition of performance as the "degree to which (an organization) realizes its goals (p.8)" However, to assess whether an organization attains its goals is no simple mater. The study of organizational—what they are, how they differ, who sets them, whether they reflect what the organization is attempting to do—reveals a frustrating history. The relationship between these studies and measuring organizational performance is explored by Hall (1991) and Scott (1977).

With respect to the HMOs in this study's sample, the assumption is made that the most important HMO goal is high quality of medicial care. Quality of care defined by the extent to which the desired health is obtained.

1. Quality of Care

The problems encountered in attemptiing to evaluate the quality of care which, on the aggregate, partients receive in a medical organization are obviously very complex and difficult. No uniform standards are available for this purpose; nor is there consensus in this field about sources and kinds of data that are concurrently necessary, sufficient, and feasible.

Eschewing the controversy over whether medical quality should be judged in terms of structure, process, or outcomes (Donabedian 1966), I adopt a definition of quality that parallels that of Georgopoulos and Mann (1962): the overall quality of care is equivalent to the average perception of quality by personnel in the HMO. This study, however, specifically seeks to distinguish better-care HMOs from those where care is of relatively lower quality. For this purpose, it is sufficient that the measures be such as to permit one to rank-order HMOs from "best" to "poorest," although in absolute terms the "poorest-care" HMO may still deliver patient care satisfactorily from a medicial standpoint. In other words, I differentiate between better- and poorer-care HMOs, not necessarily between "good" and "bad" ones.

DATA AND METHOD

Data

This study use survey data taken from the study "Organizational Structure

TABLE 1. DISTRIBUTIONS OF HMO POPULATION AND SAMPLE ACROSS THE SIXTEEN-CELL STRATIFICATION GRID

	Plan size							
Zelten plan type	Under 20,000				20,000 or more			
	Population	Sample	Response	Weight*	Population	Sam;e	Response	Weight*
I	2	2	2	0.350	3	3	2	0.350
II	3	3	2	0.350	6	4	3	0.524
III	23	6	6	1.340	13	4	3	1.135
IV	4	4	3	0.350	3	3	3	0.350
V	18	5	4	1.258	6	4	2	0.524
VI	15	4	3	1.309	15	4	3	1.309
VII	35	6	4	2.045	16	5	3	1.121
VIII	19	5	3	1.329	2	2	2	0.350
Total	119	35	27		64	29	21	

*Normed weight.

of Health Maintenance Organizations" carried out by the National Center for Health Services Research (Hetherington, Calderone, and Smale 1983). The population includes all HMOs in the United States that began operation prior to July 1979 and still operated at the time of the survey, fall of 1980 (N = 183). From the population, 64 HMOs were sampled using a statified sample that ensured representing small and large HMOs of different forms. Table 1 shows the population (N = 183) and sample (n = 64) distributions. Among the selected sample, 64, 48 HMOs agreed to participate in interviews and provide information about their physicians and administrative staffs.[1]

Weighting

Based on the probability of selection for each stratum, I adjusted for oversampled and undersampled strata by inverse weighting. Each stratum's sampling fraction is the ratio of the sampled number of cases for a stratum to its total number of cases within each stratum. When sampling fractions are unequal, it is necessary to weight the sample to produce correct estimates for the population. Calculating correct weights involved four steps (Blalock 1979; Kish 1965).

1. Calculate the sampling fraction, $sf_i = n_i/N_i$ where n_i is the stratum sample number and N_i the total stratum number.
2. Calculate the weight for each statum sa $w_i = 1/sf_i$, in order to weight by the inverse of the sampling fraction.
3. Determaine the mean weight, $\bar{W} = (\Sigma w_i \times n_i)/N$ where N is total sample number and n_i the stratum sample number.
4. Calculate normed weights(w_i^*) for each stratum by dividing the w_i by the mean weight $\bar{W}$ in order to reproduce N_s, the true sample size.

Table 1 reports the normed weights computed for each stratu.

Method

The hypotheses tests involved the simple cross-sectional specifieation:

$$Y_i = \Sigma b_{ij} x_{ij} + e_i$$

where Y_i is the dependent variable, X_j a vector of the explanatory variables, b a coefficient vector conformable to X_i, and e_i the error term.

Multiple regression allows the simultaneous measure of two or more

[1]In the actual *computing* procedure, the listwise deletion method was applied for the data. The method left 36 out of 48 HMOs.

independent variables' effects on a dependent variable, thus revealing the amount of dependent variable variance explained by those independent variables. Such analysis also offers an appropriate estimate of net effects of those independent variables on the dependent variables by controlling other independent variables.

However, the data set may contain observations well separated from the remainder. One conventional way to handle outliers is to delete them, primarily because under the least squares method, a fitted line may be pulled disproportionately toward outliers since the sum of the squared deviations is minimized. Outliers could involve large residuals and seriously affect the fitted least squares regression function. In linear regression applied to data with a smaller number of observations, the estimators of regression are more likely to be sensitive to outliers and hence more likely to be biased. However, discarding outliers might be unwise, as they might contain unique important information on HMO population. Therefore, outliers must be carefully studied, especially when sample size is small. Robust statistical methods provide estimates less likely to be highly sensitive to outliers.

I employ influential statistics to study outliers and bootstrap regression to assign an accuracy and robustness to the estimated regression coefficients.

1. Influential Statistics

With more than two independent variables, identifying outliers by simple graphic means, such as scatter and residual plot, becomes difficult. Examination of residuals sometimes does not readily detect outliers because the least squares estimation procedure tends to pull the estimated regression response towards extreme values in either the X or Y dimension. The estimated residuals for such observations may therefore not be especially large, thus hindering the search for outliers. I turn not to statistics for identifying observations that are outlying with respect to the independent variables, the dependent variable, or both: (1) Studentized Residual, (2) Hat Matrix, and (3) DFFITS.

The traditional tool for detecting outliers examines residuals. A difficulty with residuals is that they are not all estimated with the same precision. However, computing residuals' standard errors, and dividing the residuals by these standard errors yields standardized or studentized residuals. Studentized residuals are use to detect particularly, extreme Y observations (Wasserman and Katner 1985). They follow Student's t distribution with n-p-1 degrees of freedom, where n is the number of observations in the data and p the number of independent variables.

To identify Y outliers, I examined the studentized residuals for large

absolute values and used the appropriate t distribution to ascertain how far in the tails such outlying values fall. In this study, observation 1 for the dependent variable—quality of care—has the largest absolute studentized residual(–1.847). Considering tail areas of 0.05 on each side extreme, I compare the absolute value of the studentized residual with $t_{(.95:31)} = 1.697$. Based on this comparison, observation 1 for quality of care is extreme enough to warrant study.

The least squares residuals can be expressed as a linear combination of observations gi as a function of the hat matrix H:

$$e = (\mathrm{I} - H)Y$$

The hat matrix, H, is given by:

$$H = X(X'X)^{-1}X'$$

The hat matrix statistic identifies outlying X observations. The individual diagonal values of the matrix, often denoted h_{ii}, indicate the leverage of each observation, a standardized measure of how far an observation is from the center of the X observations (Wasserman and Katner 1985; SAS Institute 1990). The diagonal element h_{ii} in the hat matrix is called the leverage (in terms of the X values) of the ith observation. It indicates whether or not the x values for the ith observation are outlying, because h_{ii} depicts the distance between the x values for the ith observation and the means of the x values for all observations. Thus, a large leverage value h_{ii} indicates that the ith observation is distant from the center of the X observations. Observations with high leverages, indicated by large h_{ii}, are potentially influential, estecially if they are also outliers in Y observations as indicated by studentized residuals. A leverage value h_{ii} is usually considered large if more than twice as large as the mean leverage value, denoted by $\bar{h}$:

$$\bar{h} = \frac{\Sigma h_{ii}}{n} = \frac{p}{n}$$

where p is the number of regression parameters in the regression function including the intercept term and n the total number of observations in the regression. Hence, leverage values greater than $2p/n$ are considered by this rule to indicate outlying observatons with regard to the X values. Observation 1 has the largest leverage value $h_{ii} = 0.321$. It exceeds the criterion of twice the mean leverage value, $2p/n = 2(5)/36 = 0.278$.

It reamins to determine whether outlying observations 1with respect to X and Y values influence the regression function. DFFITS as a prime indicator

of influence statistics measures the difference between predicted values of the *i*th observation obtained by the regression estimated by all observations and that estimated by all except the *i*th(Belsley, Kuh, and Welsch 1980: Rousseeuw and Leroy 1987). Belsley and colleagues (1980) suggest that DFFITS values exceeding $2(p/n)^{1/2} = 2(/36)^{1/2} = 0.745$ in absolute value provide a convenient criterion for identifying influential observations. Observation 1 for quality of care has the largest DFFITS value (1.322), the next largest ($DFFITS_{36} = 0.760$) being substantially smaller.

DFFITS depends on two factors: (1) the size of the studentized residual and (2) the leverage value in the hat matrix. The larger of either the studentized residual or the leverage value is, the larger DFFTIS. Thus, the *i*th observation can be influential by having (1) a large studentized residual and only a moderate Hat matrix leverage value, (2) the inverse, or (3) large values on both as for quality of care.

The above three measures identify that, while coordination, an endognous variable, has no outlier of significat influence on the fitting function, one influential outlier appears for the dependent variable: observation 1 for quality of care.

2. Bootstrap method

The bootstrap method allows one to calculate robust estimates of the variance of regression estimates from a single sample's data. An obvious occasion when a robust statistical method is important is when outliers appear, particularly with a small number of observation. Extreme observations clearly have an extreme effect on sample variance. When estimating regression model parameters but concerned about outliers, robust statistical methods, which are not likely to be sensitive to outliers, are advisalbe. Efron (1979) introduced the bootstrap method, which uses computational power to get numerical estimates, since then explored by him and his colleagues (Diaconis and Efron 1983; Efron and Tibshirani 1991).

Because it has been computaionally practical for a comparatively short time, the bootstrap method has undergone little theoretical development. The algorithm relies on the notion of a bootstrap sample, which is a sample of n drawn with replacement from the original data set $x = (x_1, x_2, \cdots, x_n)$. The bootstrap sample is denoted $x^* = (x^*_1, x^*_2, \cdots, x^*_n)$. Each x^*_i is one of the original X values, randomly selected. The distribution of bootstrap sample estimates can be treated as that of real samples: it depicts the statistical accuracy of original sample estimates. As noted, the logic underlying the bootstrap method is as follows: the law of large numbers guarantees that statistical estimators calculated for large samples will very likely approach

the true values for the population. The bootstrap method surmounts the need to assume that the data conform to a bell-shaped curve and to focus on statistical measures whose theoretical properties can be analyzed mathematically.

In effect the computer assigns a number to each HMO, and then generates samples by matching a string of random numbers. The samples thus generated are called bootstrap samples. The distribution of bootstrap sample regression coeffiecients is treated as if from real samples: it estimates the statistical accuracy of the b value. The present study generated 1,000 bootstrap samples from the data for the 48 HMOs.

Worth noting is that statistical accuracy cannot be defined simply as the accuracy of an individual estimate, that is the difference between the estimate and the b's true value. Statistical accuracy refers to the average magnitude of the deviation of the estimate from the true vale. Thus, the bootstrap methods main theoretical thrust is toward confidence intervals. I use confidence intervals within one standard deviation as Diaconis and Efron (1983) and Efron (1979) suggest. They report that the interval associated with the bootstrap distribution and the interval associated with the distribution of the real samples are nearly the same width. The interval that includes 68% of the samples are recommended because for a bell-shaped curve 68% of the samples lie within one standard deviation of the peak of the bell. If the one standard deviation confidence interval contains zero, the true value of the estimate could be zero. In other words, any possibility that the true value is zero implies that the independent variable does not affect the dependent variable.

ANALYSIS AND FINDINGS

Coordination

I hypothesized positive effect for formalization and decision-making participation on HMO coordination. Table 2. displays the results of ordinary least squares (OLS) and bootstrap regression equation which support those expectations. OLS shows a 0.274 unit increase in the mean of the coordination index for every unit increase in the formalization index when differentiation and decision-making participation are held constant. A positive effect, also, appears for decision-making participation on coordination, controlling for formalization and differentiation.

These findings are more clear when the results of the bootstrap regression are viewed. The 68% confidence intervals of the coefficients do not contatin zero, which suggests formalization and decision-making participation have

TABLE 2. THE EFFECT OF FORMALIZATION, DECISION-MAKING PARTICIPATION, AND DIFFERENTIATION ON COORDINATION (N = 36)

Independent variable	OLS[a]		Bootstrap	
	b(se[b])	t-value	b(SD[c])	68% confidence interval
Formalization	0.274(0.120)	2.288**	0.264(0.128)	0.136 < b< 0.392*
Centralization	0.217(0.085)	2.535**	0.229(0.097)	0.132 < b < 0.326*
Differentiation	0.004(0.015)	0.259	0.003(0.014)	–0.011 < b < 0.017
Intercept	0.776(0.520)		1.818(0.542)	
R^2	0.338***			
Adjusted R^2	0.276			

[a]Ordinary least squares.
[b]Standard error.
[c]Standard deviation.
[d]Measured by participation in decision-making.
***p < 0.01, **p < 0.05, *p < 0.10.

TABLE 3. THE EFFECT OF HMO[a] MODEL TYPE ON QUALITY OF CARE

Independent variable	OLS		OLS without outlier		Bootstrap	
	b(se[b])	t-value	b(se)	t-value	b(SD[c])	68% confidence interval
Staff	0.180(0.208)	0.866	0.030(0.222)	0.135	1.043(0.251)	–0.211 < b < 0.291
Group	0.014(0.171)	0.081	0.039(0.190)	0.207	0.052(0.216)	–0.164 < b < 0.268
Intercept	4.449(0.134)		4.367(0.152)		4.355(0.197)	
R^2	0.027	0.001				
Adjusted R^2	–0.032	–0.044				
N	36	35				

[a]Health Maintenance Organization.
[b]Standard error.
[c]Standard deviation.

true effects on coordination.

Quality of Care

Table III shows the results of the regression analyses for quality of care on HMO types. Two dummy variables represent three HMO types. In this analysis the STAFF and GROUP models are present and the IPA model suppressed. Thus, equation intercepts imply the mean score of IPA model in quality of care, while the coefficients of STAFF and GROUP models predict the mean difference with IPA in terms of quality of care. None of the three regression equations–OLS, OLS deleting one outlier, or bootstrap–show statistically significant differences.

TABLE 4. THE EFFECT OF FORMALIZATION, CENTRALIZATION, DIFFERENTIATION, AND COORDINATION ON QUALITY OF CARE

Independent variable	OLS		OLS without outlier		Bootstrap	
	b(se)	t-value	b(se)	t-value	b(SD)	68% confidence interval
Formalization	0.179(0.164)	1.094	0.134(0.152)	0.885	0.117(0.162)	–0.045 < b < 0.279
Centralization[a]	0.163(0.119)	1.364	0.262(0.124)	2.119**	0.259(0.138)	–0.121 < b < 0.397
Differentiation	–0.023(0.019)	–1.215	-0.032(0.017)	–1.877*	–0.032(0.018)	–0.050 < b < -0.014
Coordination	0.133(0.225)	0.591	-0.017(0.226)	–0.077	–0.016(0.219)	–0.235 < b < 0.203
Intercept	3.516(0.773)		4.2467(0.820)		4.303(0.827)	
R^2	0.194		0.258**			
Adjusted R^2	0.090		0.162			
N	36		35			

[a]Measured by decision-making participation.
**p < 0.05. *p < 0.10.

For OLS regression (Table 4), decision-making participation and coordination exert positive effects on the quality of care index. Differentiation shows a negative effect (–2.023). However, none of these are statistically significant. The coefficient of multiple determation for this multiple regression is 0.194. Table 4, also, presents results of regression deleting the observation 1 outlier as well. Controlling for the other three structural variables, formalization has a positive but statistically nonsignificant effect on quality of care. Decision-making participation has a positive and significant effect on quality of care. In addition, differentiation shows a negative and statistically significant effect. But, coordination exercises a negative but statistically nonsignificant effect. Deleting the outlier improves the model coefficient of multiple determination from 0.194 to 0.258, which is statistically significant at the 0.04 level.

Bootstrap regressions in Table 4 show the 68% confidence intervals of the true values of decision-making participation and differentiation do not contain zero, while those of formalization and coordination do. These results show the same patterns as the regression equation without the outlier and strengthen the robustness of the OLS estimates that exhibited marginal significance.

Table 5 contains regression estimates for the coordination/differentiation interaction term as well as the other structural variables. Again, the effects of each variable reflect all others being held constant. For OLS regression, formalization, decision-making participation, coordination/differentiation interaction positively affect quality of care. Differentiation and coordination have negative effects. However, Table 5 OLS regression estimates are not

TABLE 5. THE EFFECT OF FORMALIZATION, CENTRALIZATION, DIFFERENTIATION, COORDINATION, AND INTERACTION BETWEEN DIFFERENTIATION AND COORDINATION ON QUALITY OF CARE

Independent variable	OLS		OLS without outlier		Bootstrap	
	b(se)	t-value	b(se)	t-value	b(SD)	68% confidence interval
Formalization	0.170(0.166)	1.027	0.113(0.146)	0.771	0.089(0.146)	0.059 < b < 0.237
Centralization[a]	0.138(0.124)	0.245	(0.119)	2.049**	0.258(0.149)	−0.109 < b < 0.407
Differentiation	−0.166(0.190)	−0.874	−0.370(0.187)	−1.982*	−0.345(0.203)	−0.548 < b< -0.142
Coordination	−0.761(1.203)	−0.633	−2.145(1.191)	−1.801*	−1.976(1.282)	−3.258 < b< 0.694
Differ * Coord	0.041(0.054)	0.757	0.096(0.052)	1.817*	0.088(0.057)	0.031 < b < 0.145
Intercept	6.695(4.272)		11.897(4.285)		11.402(4.522)	
R^2	0.209	0.332**				
Adjusted R^2	0.077	0.221				
N	36	35				

[a]Measured by decision-making participation.
**p < 0.05. *p < 0.10.

statistically significant even though in the directions predicted.

Table 5 regressions without the outlier and by bootstrap enhance conventional OLS findings. The Table V regressions without the outlier show significance at the 0.1 level for all independent variables except formalization as well as for the interaction term. In each case controlling for the other structural variables, decision-making pacticipation positively effects quality of care. Decision-making participation's effect is statistically significant at the 0.05 level, not apparent with basic OLS. The difference in R^2 without and with the interaction term shows that introducing the interaction term explains an additional 7.4% of the variance. The F ratio of the test for the increment in the proportion of variance the interaction accounts for is 3.30, nonsignificant at the 0.05 level, but significant at 0.10.

The differentiation/coordination interaction coefficients in Table 5 are as estimates of "conditional effects"–the change in the quality of care associated with a unit increase in coordination under the condition that differentiation is equal to zero. Thus, with higher differentiation, coordination positively influences quality of care, and with low differentiation, coordination affects in negatively, controlling for formalization and decision-making participation.

The bootstrap 68% confidence intervals in Table 5 show that the true values for the estimates of the structural variables except formalization are not zero. Again, these results confirm and fortify the estimates based on regression equations without the outlier.

SUMMARY AND DISCUSSION

Three steps analyze the effects of structural fators on HMO quality of care. The first step examines effects of formalization and centralization on coordination, controlling for diffeentiation. The second step explores the effects of all structural factors as well as coordination, posited to exert an intermediate as well as independent effect on performance. Finally, the differentiation/coordination interaction effect is examined, with all other structural characteristics controlled.

In the third step, formalization shows marginally significant effect on quality of care, unlike the other independent variables, including the interaction. The differentiation/coordination interaction term suggests their significant effects on quality of care are conditional. The positive influence of the interaction term on quality of care demonstrates that high HMO differentiation accompanied by high coordination has a positive effect. Based on the findings of the analyses with and without the differentiation /coordination interaction term, I conclude that the third analysis which is the theoretical model explains the relationships between structural factors and quality of care pretty well.

The assumption underlying HMOs is that, by controlling staff decisions and behaviours, they deliver good quality of care. The study renders that this assumption seems to work. Formalization, measured by job specificity, tends to positively affect quality of care even if the effect is marginal, and contributes positively to achieve coordination. By promoting decision-making participation concerning, for instance, new program and policy, and staff hiring and promotion, HMOs improve coordination and quality of care. Decision-making participation seems to encourage members to learn and hence to act on HMO goals.

Better quality of care apparently requires that different jobs or departments within an HMO work together. The HMO with the high differentiation needed to provide good quality of care faces an integration problem. HMOs where diverse services are perceived to be well-coordinated show good quality of care which could not be a product of one profession or department.

The above findings and discussion yield there suggestions for HMO management. First, decision-making participation is the most powerful structural factor affecting the HMO *raison d'etre.* HMOs best accomplish their goals—high quality care—by letting menters participate in the strategic decision-making. Second, formalization, which limits member discretion,

contributes significantly to perceived coordination. Therefore, formalization that specifies what one has to do should be implemented carefully. Finally, to achieve good quality of care, it is important that coordination must accompany differentiation. In other words, either simply providing more services or trying to achieve higher coordination may not be sound management for promoting good quality of care.

Important caveats surround secondary data analysis. My ability to generalize results is limited since I could not adjust for HMO enrollee differences. Quality of care is inevitably influenced by enrollee demographic composition, preexisting medical conditions, and related factors. Further, other HMO structural factors (e.g., profit vs. nonprofit) that may significantly affect quality of care in health care organizations are not considered, which confines generalization as well.

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