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Hospital Resource allocation in Catalonia: Activity-based financing and yardstick competition

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Abstract

The design of hospital payment systems represents a critical issue for any health insurer. The incentive propertive of any payment scheme require close analysis. The precise dose between prospective and retrospective is the most critical issue since heterogeneity in hospital capacity and case-mix makes difficult any adjustment. This paper is aimed to the design of an inpatient payment system that takes into account the heterogeneity of hospitals in a closed system. Hospitals are classified according to two dimensions: structure and case-mix. The structural classification is the result of the estimates using Grade of Membership analysis. The case-mix index allows the identification of patterns of patients treated. Both dimensions are estimated for a Catalan Public Utilization Network of 60 hospitals and are applied in a blended payment system for contracting. An assessment of the implementation experience from 1997 shows the opportunities for improvement for this model and its role in the future.

Keywords. Hospital Costs, Reimbursement, Grade of Membership Analysis

JEL classification number: I10, I18.

Introduction

Hospital payment has been evolving towards mixed payment systems over the last decade. Many countries allocate resources to hospitals based in part on their output of treated cases, although this trend takes many different forms. Examples of blended payment systems include Germany, Italy, France, Spain, Portugal, Singapore, Australia, and the Nordic countries. A well known example of an adjustment based on facility characteristics is Medicare's indirect teaching adjustment – which is based on each hospital's ratio of residents to its bed size.

Thus, in addition to case mix, it is widely recognized that payments should recognize the cost effects of exogenous factors that affect hospital costs. Hospital cost variations are related to: patient volume, patient types treated (case-mix intensity), price of inputs, hospital roles (e.g., teaching, sole community, inner city) and relative efficiency.

The Prospective Payment System (PPS) created for the U.S. Medicare system in the '80s was a radical change from the previous retrospective cost based reimbursement systems. PPS created a "price structure" (relative values) for acute inpatient hospital stays which adjusted for case-mix using 473 Diagnosis Related Groups (DRGs) (Pettengill and Vertrees (1982)). The system also adjusted prices (by adjusting each hospitals' base rate) for such factors as hospital function (e.g., teaching vs. non-teaching hospitals) and geographic cost variation. Thus, it tried to take into account at least some of the exogenous factors driving hospital costs. The adjustments in PPS explained about 67 % of hospital variation in the average operating cost per case (Jencks and Dobson (1985)). Since then, the original system has been criticized and reformed slightly. The US experience has had a relevant impact in several countries. Currently, for example, Italy, Norway, Ireland and Catalonia have adopted mixed payment systems that use case-mix adjustment.

Hospitals are complex organizations that are both structurally and functionally heterogeneous. Hospital budgets are functions of both fixed costs - related to structural factors, and variable costs - related basically to case-mix (i.e., the patient care functions the hospital performs in a total health care system). Hospital role can affect both fixed and variable costs. For example, Medicare's teaching adjustment recognizes that teaching intensity is associated with higher patient care costs (variable costs) while the sole community hospital exemption was more related to the necessary presence of underutilized technologies (fixed costs). In publicly funded health systems, payment systems must reflect both the effects of hospital structure and required function as defined by public policy planners. Hospital structure (e.g., capital, equipment; bed size) is created to support certain activities and this structural decision impacts on future expenditures. Hospitals also focus on specific clinical activities which are characterized here as the functional role of case-mix. Thus, the accurate classification of hospitals on both structural and functional dimensions is important in defining payment systems.

In this paper we assess the relationship of various structural dimensions of hospitals in Catalonia and explain the payment system that started in 1997. Previous efforts to categorize hospitals by structure were limited by analytic techniques available (Thomas et al (1983) and Trivedi (1978)). For example, both cluster analysis, and Automatic Interaction Detection algorithms have been used to maximize between group variance on selected criteria. The hospital categories generated in those analyses do not explicitly recognize variation within hospital classes, i.e., in those classifications each hospital belongs in one of a finite set of mutually exclusive, discrete homogeneous categories. This difficulty in “drawing lines” between clearly different types of hospitals is the reason that the indirect teaching adjustment is continuous – based on an average cost function.

In this study we use Grade of Membership analysis, a multivariate procedure, to classify hospitals into 'fuzzy sets' (Vertrees and Manton (1986) and Woodbury, Manton and Vertrees (1992)). Fuzzy sets allow for variation of hospital characteristics within analytically defined hospital categories by assigning convex scores or weights which describe the degree to which the characteristics of a hospital are defined by the profile of characteristics defining a particular hospital "set" or "class". A particular hospital may belong to several classes; for example, 70% like a teaching hospital and 30% like a sole community provider.

In the analysis, five groups were formed from 60 variables related to hospital structure. Cost was not used as a criterion for forming groups, i.e., we wished to categorize hospitals by structural characteristics independent of budget because budgets are influenced by exogenous factors, not related to hospital structure or function, which make the relationship of structure or function to budget ambiguous.

The evolution towards yardstick competition

At mid '90s the Catalonia Government decided that there was a need to reform the system which was, at that time, based on Basic Care Units, a payment system related to bed days and their equivalents for ambulatory care. A commission was created to develop a new system. The results were implemented (with some delay) during 1997. However one should consider 1998 as the first year that the new system was really in place.

The goals of that system were to improve efficiency, fairness in funding providers, allow budgetary prediction and guarantee financial sustainability. An increase in information transparency required new information systems.

The current hospital network in fact creates local monopolies. One goal was to avoid competition between the hospitals within the public funded network. In such environment, there is a need to find a precise framework which allows a fair assessment of each hospital performance. The theoretical foundation of such system can be found in the "yardstick competition" concept from Shleifer (1985). Yardstick competition is a regulatory scheme that rewards regulated firms on the basis of their performance as compared with the performance of similar firms in the same sector. If a regulated firm, a hospital in our case, is more efficient than the firms to which it is compared, it will make more than normal profits. Spain's traditional cost-of-service regulation does not provide incentives for promoting efficiency since the internal prices are primarily based on historical cost. In schemes like yardstick competition, firms bear greater risks as they can make a profit or loss. As a compensation for this risk, they are also able to retain the profit they generate.

Shleifer (1985) considers that what regulator needs is a different reference from previous or actual results from the firm to assess its potential for efficiency. Therefore there was a need to use cost for comparable firms and the problem for us is to define "comparable". At a first stage he assumes away this key problem by assuming identical firms, risk-neutrality, uncertainty environment, and same demand curve in separate markets. Shleifer (1985) considered initially the same marginal costs and the same technology to reduce costs and the regulator could make transfers directly to them. In his models profits are modelled as: $P=[(p-c)*q(p)]-R(c)+T$, where P were profits, p prices, c marginal cost, q quantity, $R(c)$ cost-reduction expenditures, and T transfers or subsidies from the regulator.

If $\underline{R(c)}$ were known by the regulator, the welfare maximization problem would be reduced to achieve that $\underline{B}$ was greater or equal 0. Optimization conditions for this problem would be that $\underline{p^*=c^*}$, price equal marginal cost, and $\underline{R(c^*)=T^*}$, or the marginal cost in cost reduction efforts were equal to marginal benefit in cost reduction effort. When such effort is unknown by the regulator we should take as a reference equivalent hospitals. And since we can't make a transfer according to such effort, Shleifer (1985) proposes a payment according to average costs.

However, hospitals are not homogeneous and the regulator is not able to distinguish exogenous factors which influence costs easily. Taking into account such differences we could introduce a regression of costs according to characteristics that determine heterogeneity.: $\underline{C \approx m+b\theta}$, where $\underline{C}$ is the firms' cost level and the last term reflects exogenous features. Regulator establishes a price equal to mean expected cost plus an amount according to differential characteristics of the hospital. If the regulator is able to observe which factors determine such heterogeneity our objective could be achieved.

With this foundation the Catalan system was build according to lines of activity: - inpatient, outpatient, emergency, procedures, teaching and research. For each line a parameter for buying activity was decided: discharge, visit package, emergencies and detailed procedures. In inpatient care exogenous features include available standby capacity (structure) and case-mix. Therefore discharges will be adjusted according to these variables.

Data

A specific survey was designed that included 60 variables on hospital structure. The list of these variables is included in table 1, reflect capacity available for production.

Hospitals belonging to Public Hospital Utilization Network in Catalonia were the target of the analysis. The number of participating hospitals was 60. These hospitals are mostly publicly funded by Catalan Health Service. Therefore, the analysis was focused on the publicly funded inpatient care.

(Table 1)

Methods

There are several methodologies that might be used to classify complex, heterogeneous objects with characteristics described by multivariate categorical data. For example, factor and cluster analysis have been used to classify catalan (Departament de Sanitat i Seguretat Social. Gabinet Tècnic (1983)) and spanish hospitals (López-Casasnovas (1984)).

The classification procedure used here is "Grade of Membership" (GoM) analysis. GoM has several advantages over the techniques previously used. Factor analysis only uses information contained in the correlation or covariance matrix of hospital characteristics. If the data are not normally distributed (like many of the structural variables), there is significant information in higher order moments which factor analysis cannot use. Cluster analysis procedures are defined by the statistical measure of "distance" used to describe "similarity". It is difficult to define a classification metric from multiple variables, which has a "natural" interpretation. In addition the effect of missing information was severe.

GoM avoids these problems. It can utilize moments up to order J, i.e., the number of variables. It does not have the measurement theoretic problems of cluster analysis because its solution is identified by the intersection of the space of all possible response vectors, M, for the J variables selected for analysis, and the linear space L_B containing the probabilities of specific responses calculated from model parameters. The intersection of the response space and the fitted probability space (i.e., $L_B \cap M$) defines B, the solution space whose K vertices are defined by the coordinates (λ_{kjl}) of the hospital types in the space of J variables analysed; and by the K half spaces linking the K vertices -- which define the weights (g_{ik} scores) for each hospital relative to each of the hospital types. That is, one interpolates between the K extreme types of hospital to choose the weights that best match the (ith) hospital. A mathematical description of the model, and its statistical properties, is presented elsewhere (Woodbury and Clive (1976, 1978) and (Tolley and Manton (1992)). Hence, below we restrict our description to properties relevant to hospital classification.

Four features can describe the model. The first is the representation of the data. Each data element is coded as a binary (0,1) variable y_{ijl} that describes if the ith observation ($i=1,2,...,I$; here the 60 hospitals) has the lth ($l=1,2,...,L_j$) response to the

jth ($j=1,2,...,J$) variable. Each continuous variable is coded into a set of L_j binary variables. Selecting the number and interval boundaries of L_j categories to represent a continuous variable is a preliminary step in preparing data for analysis.

A second feature is the number of types or classes of hospitals necessary to explain the y_{ijl}. This quantity is first specified external and the analysis conducted to determine if all non-random variation in y_{ijl} is explained by the pre-specified number of types, K. This is done by calculating the likelihood ratio for models with K, and $K+1$ types, and seeing if the additional type is significant.

The third feature of the model is the description of the y_{ijl} by K analytically determined classes or types, where each types is defined by two sets of coefficients. The first, λ_{kjl}, is the probability that an observation (here a hospital) which is exactly characterized by the kth type ($g_{ik}=1.0$), has the lth response to the jth variable. The probabilities add to one for all the outcomes of each of J variables.

$$\sum_{l=1}^{L_j} \lambda_{kjl} = 1.0 \tag{1}$$

meaning that an observation can have only one of the L_j possible responses to the jth variable, i.e., each of the J variables is multinomially distributed. The λ_{kjl} are the coordinates for the hospital of type k and in the solution space B. The second type of coefficient, the g_{ik} scores are weights used to interpolate the characteristics of the ith hospital which are represented by the characteristics associated (indicated by the λ_{kjl}) with the kth type to guarantee that the observed distribution of attributes, y_{ijl}, is closely matched by the GoM model, the correct number of hospital types has to be found. The constraints on the g_{ik} define a convex set, i.e., they are in the range 0 to 1.0 (i.e., $0.0 \le g_{ik} \le 1.0$) and add to 1.0 for each observation. This convexity constraint also means that the $g_{ik}s$ can be used as "blending" coefficients to generate hospital rates that are continuously weighted mixtures of the rates for the hospital classes.

With these definitions, the final features of the model is that predicts the probability, p_{ijl}, that the ith hospital has the lth response to the j variable, as,

$$p_{ijl} = PROBABILITY(y_{ijl} = 1.0) = \sum_{k=1}^{K} g_{ik} \lambda_{kjl}$$

(2)

To estimate $g_{ik}s$ and λ_{kjl}, maximum likelihood estimation is used. These procedures iteratively search for values of g_{ik} and λ_{kjl} that maximize the value of the likelihood, or,

$$L = \prod_i \prod_j \prod_l (\sum_k g_{ik} \lambda_{kjl})^{y_{ijl}}$$

(3)

Because coefficients are estimated by maximum likelihood, the statistical properties of the parameters (i.e., consistency of g_{ik} and λ_{kjl}; the χ^2 distribution of the ratio of two likelihood values under boundary constraints; identifiability of parameters; both necessary and sufficient conditions for identifiability) are well characterized (Tolley and Manton (1991) and Manton, Woodbury and Tolley (1993)). The ability of the model to describe hospital characteristics (the y_{ijl}) is measured by χ^2 generated from the ratio of likelihood values for models with K and $K+1$ types.

The coefficients of the GoM model can be further understood by comparing it with other methods used to describe multiple categorical variables. For example, log-linear models (Bishop, Fienber and Holland (1975)) are often used to analyze the frequency of the lth response to the jth variables for each of K independent populations. The frequencies define cell probabilities, say λ_{jl}, for a J-way contingency table. If the K independent groups within which each case falls are known, then one can define the observed classification variable, g_{ik}=1 or 0, and K sets of λ_{jl} (i.e., λ_{kjl}) can be independently estimated.

Often the K groups are not observed, or are only known with error. In this case Latent Class Analysis (LCA) (Lazarsfeld and Henry (1968)) can be used. In LCA the g_{ik} are still required to be 0 or 1 but they are not observed and must be estimated simultaneously with the λ_{kjl}. Often, instead of estimating g_{ik}, the Bayesian posterior probability of being in the Kth group (i.e., p_{ik}= *(Prob=1.0)*) is estimated instead.

GoM generalizes LCA by allowing the $\underline{g_{ik}}$, to vary between 0 and 1. This means GoM can represent and additional component of heterogeneity not in LCA, i.e., within class heterogeneity of individuals. Thus, LCA is parametrically nested within (i.e., is a special case of) the GoM model and the performance of the two models can be tested sing likelihood ratio principles. The $\underline{g_{ik}s}$ define the location of an observation relative to the classes of hospitals each defined by a set of $\underline{\lambda_{kjl}s}$. For a given $\underline{K}$, hospitals are adequately described in LCA if there is no significant heterogeneity between hospitals in a group. As GoM directly represents hospital heterogeneity by the $\underline{g_{ik}}$, the number of classes needed to describe any set of hospitals is less than in LCA, with within group heterogeneity represented by $\underline{g_{ik}s}$. In analyses where both procedures were applied to a common data set, for a given $\underline{K}$ and relatively large $\underline{J}$, the GoM procedure provided better predictions, and substantively more meaningful class definitions than LCA.

Results

Hospital classification

Sixty variables selected from the 'Hospitals Survey' were used in the analysis. Tests of different values of $\underline{K}$ indicated the $\underline{K}$=5 was the "best" number of classes, i.e., gave the best likelihood ratio χ^2 relative to the number of parameters fitted. The five sets of coefficient estimates, $\underline{\lambda_{kjl}}$ are in Table 3. These five profiles are the minimum number needed to explain differences between the 60 hospitals on the 60 characteristics (Table 2).

[Table 2 about here]

In table 3 we see that there is a column for the sample proportion for each variable, e.g., for the first variable, Medicine Beds, 11.67% of hospitals had between 1 and 22. In order to read the table, lets present an example. If a hospital has a grade of membership 1 to pure type 1, then it will have a probability of 33,3% of having between 1-22 Medicine Beds. Any hospital $\underline{g_{i1}}$=1 will have less than 110 Medicine Beds.

The hospital types can be characterized as:

1. "Small facilities". Basic Hospitals, less than 133 beds, and limited scope of technologies available.
2. "Medium-sized facilities". County Hospitals, 133-261 beds, essential technologies available.
3. “Reference Hospitals”, 262-450 beds, advanced technologies available
4. “Teaching Hospitals”, 450-655 beds, advanced technologies available.
5. "Teaching and High Tech Hospitals" , more than 655 beds, high technologies available.

Table 4 shows the distribution of $g_{ik}S$ for each type and, in table 5, the distribution of grades of membership across types.

[Table 3 and 4 about here]

On the first three elements of the diagonal in the bottom of the table are the number of hospitals described by one type, i.e., 11 hospitals have a g_{i1}=1.0 and a g_{i2}=1.0, 8 hospitals have a g_{i3}=1.0, and 4 hospitals have g_{i4}=1.0 g_{i5}=1.0 . Forty-two hospitals are defined by only one pure type.

Discussion

Yardstick competition is a new development that show promising features for resource allocation because existing DRGs-Prospective Payment Systems often fail to explain an adequate amount of cost variation. This is because structural and functional characteristics of hospitals are not adequately represented in DRG prices. In the future, global resource allocation methods may also be used for internal management. Case-mix adjustment can easily be introduced in a GoM application by modifying the methods in this paper. The GoM analysis presented here uses the hospital as a unit of observation. We did not attempt to examine case mix variation within the hospital because the necessary information on individual patients was not available for this research.

Fixed costs and technology drive a crucial part of resource use in hospitals. GoM analysis allows us to predict resource use, using structural and functional characteristics of hospitals to define the role the hospital is equipped to play. These predictors can be compared to observed costs. Identifying hospitals where actual costs differ greatly from expected costs is extremely useful for management decisions at a global level in a health service system. Allocations based on discrete classification criteria are improved in GoM using a continuous weighting of facilities to calculate rates and budgets.

The hospital classification model can be made dynamic if the structural and functional characteristics of the hospital change and are measured at multiple times, t. In this case, scores are calculated for each hospital at a measurement time (i.e., g_{ikt}) and a time series analysis of the $g_{ikt}s$ performed to produce an estimate of a change function (e.g., $g_{ikt+1}=C_t \cdot g_{ik}+e_{ik}$; C_t is time dependent) to forecast future costs as each hospital's structure and functional role evolves with time. Planners could use or modify this information as needed given demographic and other trends.. This could be done by adding in exogenous factors, z_{im}, i.e.,

$$g_{ikt+1} = C_t g_{ik} + \gamma_t z_{im} + e_{ik} \tag{4}$$

or by restricting the exogenous factors to operate directly through the g_{ikt}, i.e., a simultaneous equation system is estimated,

$$g^*_{ik} = \Gamma z_{im} + e_{ik} \tag{5}$$

and

$$g_{ikt+1} = C^{*t} g^*_{ik} + e^*_{ik} \tag{6}$$

A pricing mechanism as Prospective Payment System in US is not enough to provide a long-term cost-containment strategy. Structural variables that drives costs must be taken into account on payment systems. In a recent review, Newhouse (1996) suggests the adoption of mixed reimbursement systems, partially prospective and partially specific to the hospital and shows the need to introduce theoretical developments in regulation and government contracting. Incentives contracts must define at first types of firms and output. Our approach can be used as a first step in this area. The influence of structural and performance variables in predicting costs has been reported also on a research of hospital cost functions with the same data as in our study (Puig (1988)).

7. A global assesment of the results

Unfortunately there is not any individual hospital cost data series that would allow a detailed analysis of the impact of the payment system.

Conclusions

A multivariate procedure for classifying hospitals, 'Grade of membership analysis', was applied to 60 Catalan hospitals funded by the Servei Català de la Salut. Sixty structural variables from each hospital have been chosen from the year 2000 Hospital Survey. Three hospital types were defined and the membership scores of each hospital to the three types computed. Regression showed that $g_{ik}s$ explain of costs per bed and of costs per basic care unit. These findings suggest expanded possibilities for resource allocation policies in public health care systems. They allow rate setting on a multidimensional basis, identifying differences between the expected and observed cost behaviours in individual hospitals. Used in a dynamic simulation they could forecast costs for future periods.

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Table 1. Variable Descriptions

Inpatient resources	
Medicine	Number of beds
Specific programme	Number of beds
Surgery	Number of beds
Trauma surgery	Number of beds
Gynecology and Obstetricy	Number of beds
Paediatrics	Number of beds
Paedriatics surgery	Number of beds
Neonatology	Number of beds
Neonatology	Number of incubators
Neon crítics	Number of acute beds
Neon crítics	Number of beds
Critical burn	Number of beds
Coronary critics	Number of beds
Critics	Other beds
Semiintensive	Number of beds
Psyquiatry	Number of beds
	Other beds
Beds	Total Num.
Ambulatory activity resources	
Rooms	Hours/week
Urology	Hours/week
Dermatology laser board	Hours/week
Ofmatology laser board	Hours/week
Audiometry rooms	Hours/week
Endoscopy rooms	Hours/week
Doppler rooms	Hours/week
Eco Doppler rooms	Hours/week
Rehabilitation rooms	Hours/week
Day hospital beds	Hours/week
Ambulatory surgery beds	Hours/week
Emergency resources	
Specialties available	Num
Physicians available	Num
Specialties on call	Num
Physicians on call	Num
Box diagnostic and treatment	Num

Box observation	Num
Boxes reanimation	Num
Surgical area resources	
Normal surgical rooms	Hours/week
Ambulatory surgical room	Hours/week
Cardiac surgery room	Hours/week
Postsurgery reanimation beds	Hours/week
Hemodynamics rooms	Hours/week
Interventionist Rx Rooms	Hours/week
Obstetrics rooms	Hours/week
Diagnostic Imaging	
Conventional radiology rooms	Hours/week
Mammography rooms	Hours/week
Ecography rooms	Hours/week
CT scan	Hours/week
NMR	Hours/week
Radiotherapy resources	
Linear accelerator	Hours/week
E. Telecobaltoteràpia	Hours/week
Simulators	Hours/week
E. Planning	Hours/week
Gammacameras	Hours/week
U braquiteràpia	Hours/set
Teaching and research	
Pregraduate teaching	Num.
Postgraduate teaching	Places
Postgraduate Specialties teaching	Num
Other specialties	Num
Specific variables	
In-vitro fertilization Laboratory	
U. Politraumat	
Litotriptor	

Table 2. Number of pure types, degrees of freedom and value of χ^2

Number of pure types	Degrees of freedom	χ^2	Difference in freedom stages	Difference in χ^2
2	328	387	-	-
3	652	1857	324	1470
4	981	2477	329	620
5	1320	2628	335	116
6	1655	2915	335	287

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables.

I llmed	**Medicine beds**				
	Freq	I	II	III	IV
0	3.33	4.76	0.00	7.15	0.00
1·22	11.67	33.33	0.00	0.00	0.00
23·55	26.67	57.16	19.02	0.00	0.00
56·110	33.33	4.74	71.46	28.55	0.00
111·247	16.67	0.00	9.52	57.19	0.00
>247	8.33	0.00	0.00	7.11	100.00
H = 0.7287	QRF:	1.0001	1.0002	0.9997	1.0011

I llproesp	Special programmes beds				
	Freq	I	II	III	IV
0	55.00	71.43	47.61	49.99	24.97
1·7	11.67	19.05	14.29	0.00	0.00
8·14	11.67	9.52	23.82	0.00	0.00
15·26	6.67	0.00	9.52	14.29	0.00
27·64	13.33	0.00	4.76	28.57	75.03
>64	1.67	0.00	0.00	7.15	0.00
H = 0.2945	QRF:	1.0000	1.0000	1.0001	1.0000

I llquir	Surgery beds				
	Freq	I	II	III	IV
0	5.00	9.52	0.00	7.14	0.00
1·23	20.00	52.40	4.73	0.00	0.00
24·51	31.67	38.08	47.64	7.11	0.00
52·97	26.67	0.00	42.87	50.02	0.00
98·227	11.67	0.00	4.76	35.73	25.00
>227	5.00	0.00	0.00	0.00	75.00
H = 0.6198	QRF:	1.0002	1.0001	0.9999	1.0001

I llquicot	COT surgery beds				
	Freq	I	II	III	IV
0	5.00	4.76	9.53	0.00	0.00
1·10	8.33	23.81	0.00	0.00	0.00
11·23	28.33	52.40	28.55	0.00	0.00
24·43	38.33	19.02	52.40	57.14	0.00
44·109	18.33	0.00	9.52	42.86	75.00
>109	1.67	0.00	0.00	0.00	25.00
H = 0.4648	QRF:	1.0000	1.0000	1.0002	1.0002

I llginobt	Gynaecology and Obstetrics Beds				
	Freq	I	II	III	IV
0	11.67	4.76	28.59	0.00	0.00
1·6	18.33	42.87	9.50	0.00	0.00
7·13	18.33	47.62	4.75	0.00	0.00
14·23	23.33	4.74	47.67	14.25	24.99
24·43	16.67	0.00	4.73	57.18	24.99
>43	11.67	0.00	4.75	28.57	50.01
H = 0.6386	QRF:	1.0001	0.9997	1.0004	1.0000

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I llmedped		Paediatritian medicine beds			
	Freq	I	II	III	IV
0	36.67	33.33	57.19	7.04	49.99
1·3	10.00	28.58	0.00	0.00	0.00
4·8	18.33	33.35	14.28	7.13	0.00
9·18	18.33	4.75	23.80	35.75	0.00
19·69	13.33	0.00	4.73	42.93	25.00
>69	3.33	0.00	0.00	7.15	25.01
H = 0.4196	QRF:	0.9999	1.0004	0.9995	0.9999

I llquiped		Pediatrics surgery beds			
	Freq	I	II	III	IV
0	68.33	90.49	71.43	28.52	74.99
1·3	8.33	4.75	9.52	14.30	0.00
4·8	15.00	0.00	14.28	42.88	0.00
9·31	5.00	4.76	4.76	7.14	0.00
>31	3.33	0.00	0.00	7.15	25.01
H = 0.2132	QRF:	1.0001	1.0000	0.9999	0.9998

I llneonat		Neonathology beds			
	Freq	I	II	III	IV
0	61.67	76.21	76.20	21.38	49.99
1·2	8.33	9.53	9.52	0.00	25.01
3·5	10.00	4.75	9.52	21.46	0.00
6·9	8.33	4.76	0.00	28.58	0.00
>9	11.67	4.76	4.76	28.58	25.00
H = 0.2199	QRF:	0.9998	1.0001	0.9999	0.9997

I inneonat		Neonathology incubators			
	Freq	I	II	III	IV
0	33.33	28.56	52.40	14.27	25.00
1	13.33	33.36	4.73	0.00	0.00
2·4	33.33	33.32	38.11	28.56	24.99
5·13	11.67	0.00	0.00	42.88	25.00
>13	8.33	4.76	4.76	14.29	25.00
H = 0.2876	QRF:	1.0001	0.9999	0.9999	0.9998

I llcneocr		Critical neonathology incubators			
	Freq	I	II	III	IV
0	66.67	85.71	80.98	28.52	24.98
1	8.33	14.29	4.75	7.14	0.00
2·3	6.67	0.00	4.75	21.45	0.00
4·9	11.67	0.00	9.52	28.60	25.00
>9	6.67	0.00	0.00	14.29	50.02
H = 0.2842	QRF:	1.0001	1.0000	0.9999	0.9998

I llneonac		Critical neonathology beds			
	Freq	I	II	III	IV
0	85.00	95.24	90.49	64.26	74.99
1·2	6.67	4.76	4.75	14.30	0.00
3·5	3.33	0.00	0.00	14.29	0.00
>5	5.00	0.00	4.76	7.15	25.01
H = 0.1044	QRF:	1.0000	1.0000	0.9999	0.9997

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I llcremat					Critical burnt beds
	Freq	I	II	III	IV
no	98.33	100.00	100.00	100.00	74.99
si	1.67	0.00	0.00	0.00	25.01
H = 0.0474	QRF:	0.9999	1.0000	0.9999	0.9996

I llcorona					Coronary beds
	Freq	I	II	III	IV
0	76.67	95.24	80.95	64.27	0.00
1·3	5.00	4.76	4.76	7.15	0.00
4/	10.00	0.00	14.29	14.30	24.99
>7	8.33	0.00	0.00	14.28	75.01
H = 0.2389	QRF:	1.0001	1.0000	0.9998	1.0004

I allcriti					Other critics beds
	Freq	I	II	III	IV
0	46.67	90.50	42.84	0.00	0.00
1·5	13.33	4.75	33.36	0.00	0.00
6·13	23.33	4.75	23.81	57.15	0.00
14·41	11.67	0.00	0.00	42.85	25.00
>41	5.00	0.00	0.00	0.00	75.00
H = 0.6600	QRF:	1.0002	0.9998	1.0004	1.0001

I llsemiin					Semi intensive beds
	Freq	I	II	III	IV
0	75.00	95.24	85.72	42.83	24.97
1·5	5.00	4.76	4.77	7.14	0.00
6·9	10.00	0.00	9.52	14.30	50.02
10·21	6.67	0.00	0.00	28.59	0.00
>21	3.33	0.00	0.00	7.15	25.01
H = 0.2573	QRF:	1.0000	1.0001	0.9998	0.9996

I llpsiqui					Psychiatrical beds
	Freq	I	II	III	IV
0	68.33	95.24	71.43	42.83	0.00
1·11	13.33	0.00	14.29	28.58	25.00
12·26	8.33	0.00	9.52	21.45	0.00
27·68	8.33	0.00	4.76	7.14	75.00
>68	1.67	4.76	0.00	0.00	0.00
H = 0.3076	QRF:	1.0002	1.0000	0.9998	1.0001

I cceehs					CCEE hs rooms
	Freq	I	II	III	IV
1·637	20.00	42.88	14.26	0.00	0.00
638·1303	35.00	52.39	42.86	7.11	0.00
1	25.00	4.72	42.89	35.72	0.00
2	15.00	0.00	0.00	57.17	25.00
>5590	5.00	0.00	0.00	0.00	75.00
H = 0.5815	QRF:	1.0000	1.0002	0.9999	1.0001

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I urodihs				urodinamia hs rooms	
	Freq	I	II	III	IV
0	68.33	90.48	76.20	35.66	24.97
1·10	8.33	0.00	9.52	21.45	0.00
11·20	5.00	0.00	0.00	21.44	0.00
21·64	11.67	9.52	9.52	21.45	0.00
>64	6.67	0.00	4.76	0.00	75.03
H = 0.3044	QRF:	1.0001	1.0000	0.9999	0.9997

I gladehs				Derm hs Laser Board	
	Freq	I	II	III	IV
0	93.33	100.00	100.00	78.56	74.99
1·21	5.00	0.00	0.00	21.44	0.00
>21	1.67	0.00	0.00	0.00	25.01
H = 0.1238	QRF:	1.0000	1.0000	0.9999	0.9997

I glaofhs				Oft hs Laser Board	
	Freq	I	II	III	IV
0	50.00	80.97	57.14	7.09	0.00
1·19	33.33	19.03	33.34	57.17	24.99
20·48	10.00	0.00	9.52	21.45	25.01
>48	6.67	0.00	0.00	14.29	50.01
H = 0.3056	QRF:	1.0001	1.0001	0.9997	1.0000

I audiohs				Audiometry hs rooms	
	Freq	I	II	III	IV
0	15.00	23.81	19.05	0.00	0.00
1·17	36.67	52.39	38.10	21.40	0.00
18·54	36.67	23.80	38.10	57.15	24.99
>54	11.67	0.00	4.75	21.45	75.01
H = 0.2289	QRF:	1.0000	0.9999	1.0001	0.9999

I endohs				Endoscopy hs rooms	
	Freq	I	II	III	IV
0	10.00	23.82	4.75	0.00	0.00
1·17	18.33	38.12	14.27	0.00	0.00
18·59	31.67	28.57	42.87	28.56	0.00
60·176	33.33	9.49	38.11	50.01	75.00
>176	6.67	0.00	0.00	21.43	25.00
H = 0.3182	QRF:	0.9999	0.9999	1.0002	1.0001

I dopplhs				Doppler hs rooms	
	Freq	I	II	III	IV
0	55.00	95.28	52.36	14.26	0.00
1·19	26.67	4.72	38.12	42.88	24.99
20·57	11.67	0.00	4.76	28.57	50.01
58·213	5.00	0.00	4.76	7.14	25.00
>213	1.67	0.00	0.00	7.14	0.00
H = 0.3448	QRF:	1.0000	0.9999	1.0001	1.0001

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I ecdophs	Eco Doppler hs rooms				
	Freq	I	II	III	IV
0	15.00	33.35	9.51	0.00	0.00
1·29	21.67	28.58	33.34	0.00	0.00
30·97	46.67	33.32	47.62	71.43	24.98
98·286	11.67	4.76	9.53	21.43	25.00
>286	5.00	0.00	0.00	7.14	50.01
H = 0.2850	QRF:	0.9999	1.0000	1.0002	0.9998

I rehabihs	Rehabilitation hs rooms				
	Freq	I	II	III	IV
0	15.00	23.82	14.29	7.13	0.00
1·32	8.33	9.52	14.29	0.00	0.00
33·115	20.00	33.34	19.05	7.13	0.00
116·318	30.00	28.57	23.80	42.87	24.99
319·872	21.67	4.75	28.57	35.73	25.00
>872	5.00	0.00	0.00	7.14	50.01
H = 0.2323	QRF:	0.9999	1.0000	1.0000	0.9999

I plhdiahs	Hospital Day Places hs				
	Freq	I	II	III	IV
0	23.33	52.41	14.25	0.00	0.00
1·398	40.00	42.84	57.18	21.40	0.00
399·1311	23.33	4.75	19.04	64.32	0.00
·	10.00	0.00	9.53	14.28	50.01
>3216	3.33	0.00	0.00	0.00	49.99
H = 0.4413	QRF:	1.0002	0.9997	1.0001	1.0003

I plquamhs	Surgery places with hs				
	Freq	I	II	III	IV
0	25.00	42.88	9.48	7.13	75.00
1·155	26.67	38.09	33.34	7.13	0.00
156·447	30.00	19.03	42.89	35.72	0.00
448·1018	15.00	0.00	14.28	42.88	0.00
>1018	3.33	0.00	0.00	7.14	25.00
H = 0.3216	QRF:	1.0002	0.9997	1.0001	1.0000

I espresfi	Presence Specialists Fis.				
	Freq	I	II	III	IV
0	10.00	28.59	0.00	0.00	0.00
1·3	23.33	52.43	14.25	0.00	0.00
4·8	41.67	14.23	76.26	42.82	0.00
9·20	18.33	4.75	9.49	57.18	0.00
>20	6.67	0.00	0.00	0.00	100.00
H = 0.6281	QRF:	0.9996	1.0003	1.0003	1.0001

I fapresfi	Presence facultatives F.				
	Freq	I	II	III	IV
0	1.67	4.76	0.00	0.00	0.00
1·6	40.00	80.99	33.29	0.00	0.00
7·16	31.67	14.24	61.96	21.40	0.00
17·35	15.00	0.00	0.00	64.33	0.00
>35	11.67	0.00	4.76	14.28	100.00
H = 0.6361	QRF:	1.0000	1.0003	0.9998	1.0006

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I eslocali	Easy to find specialization				
	Freq	I	II	III	IV
0	5.00	9.53	4.76	0.00	0.00
1	10.00	0.00	19.06	14.28	0.00
2·4	35.00	33.33	42.87	35.70	0.00
5·9	38.33	52.39	33.32	28.57	24.99
>9	11.67	4.75	0.00	21.45	75.01
H = 0.2249	QRF:	0.9999	1.0001	1.0000	1.0000

I falocali	Easy to find facultatives				
	Freq	I	II	III	IV
0	6.67	14.29	4.75	0.00	0.00
1	10.00	0.00	19.06	14.28	0.00
2·4	31.67	28.56	38.11	35.71	0.00
5·14	45.00	47.62	38.08	50.01	49.99
>14	6.67	9.52	0.00	0.00	50.01
H = 0.1940	QRF:	1.0000	1.0000	1.0000	1.0000

I pldiatra	Urgency places diag/trac				
	Freq	I	II	III	IV
0	8.33	14.29	9.51	0.00	0.00
1·7	28.33	61.92	19.02	0.00	0.00
8·17	30.00	23.78	52.44	14.23	0.00
18·34	25.00	0.00	19.03	71.49	24.98
>34	8.33	0.00	0.00	14.28	75.02
H = 0.5181	QRF:	1.0002	1.0001	0.9998	1.0003

I plobserv	Urgency observation places				
	Freq	I	II	III	IV
0	15.00	23.82	14.27	7.14	0.00
1·4	26.67	47.64	23.79	0.00	24.99
5·15	46.67	23.77	61.93	71.43	0.00
16·50	10.00	4.76	0.00	21.43	50.01
>50	1.67	0.00	0.00	0.00	25.00
H = 0.3109	QRF:	0.9999	1.0001	1.0001	1.0000

I boxreani	Reanimation Box				
	Freq	I	II	III	IV
0	5.00	4.76	9.53	0.00	0.00
1	50.00	71.45	52.38	28.54	0.00
2·4	41.67	23.78	33.34	64.31	100.00
>4	3.33	0.00	4.76	7.15	0.00
H = 0.1508	QRF:	0.9999	0.9999	1.0000	1.0001

I qugenehs	hs operating theatres				
	Freq	I	II	III	IV
1·211	28.33	57.18	19.01	7.13	0.00
212·466	43.33	33.32	80.99	14.21	0.00
467·1013	21.67	9.50	0.00	78.66	0.00
>1013	6.67	0.00	0.00	0.00	100.00
H = 0.5905	QRF:	0.9997	1.0006	0.9995	1.0001

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I qucmahs	CMA hs operating theatres				
	Freq	I	II	III	IV
0	46.67	61.92	52.38	14.26	49.99
1·50	13.33	19.06	14.28	0.00	25.00
51·113	30.00	9.50	33.34	64.31	0.00
114·285	8.33	9.52	0.00	21.43	0.00
>285	1.67	0.00	0.00	0.00	25.01
H = 0.2684	QRF:	0.9998	1.0000	1.0003	0.9998

I qucicahs	Cardiac surgery operating theatres hs				
	Freq	I	II	III	IV
0	90.00	100.00	100.00	85.71	0.00
1·57	3.33	0.00	0.00	14.29	0.00
58·121	5.00	0.00	0.00	0.00	75.00
>121	1.67	0.00	0.00	0.00	25.00
H = 0.2934	QRF:	1.0000	1.0001	0.9999	1.0001

I plrepohs	PQ Reanimation places hs				
	Freq	I	II	III	IV
0	3.33	4.76	0.00	7.15	0.00
1·397	50.00	71.45	57.13	21.39	0.00
398·1144	30.00	23.79	38.11	35.73	0.00
·	13.33	0.00	4.76	35.73	50.00
>3106	3.33	0.00	0.00	0.00	50.00
H = 0.3191	QRF:	1.0000	1.0001	0.9998	1.0001

I sahemohs	Hemodynamics hs rooms				
	Freq	I	II	III	IV
0	86.67	100.00	100.00	71.41	0.00
1·86	8.33	0.00	0.00	28.59	25.00
87·233	3.33	0.00	0.00	0.00	50.00
>233	1.67	0.00	0.00	0.00	25.00
H = 0.3041	QRF:	1.0000	1.0001	0.9998	1.0002

I srxinhs	Rx Intervention Rooms Hs				
	Freq	I	II	III	IV
0	55.00	80.97	57.13	28.56	0.00
1·24	11.67	9.52	19.07	7.12	0.00
25·57	25.00	4.75	19.04	64.32	24.99
58·419	6.67	4.76	4.76	0.00	50.01
>419	1.67	0.00	0.00	0.00	25.00
H = 0.2888	QRF:	0.9999	1.0001	0.9999	1.0000

I saparths	Labour rooms hs				
	Freq	I	II	III	IV
0	20.00	14.28	38.12	0.00	25.00
1·168	40.00	80.98	23.79	14.25	0.00
169·336	23.33	4.75	28.58	42.87	24.99
>336	16.67	0.00	9.51	42.88	50.01
H = 0.3639	QRF:	1.0001	0.9998	1.0002	0.9999

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I saracohs	Conventional radiology rooms Hs				
	Freq	I	II	III	IV
0	35.00	57.17	42.85	0.00	0.00
1·256	48.33	38.09	57.15	57.12	24.98
257·523	11.67	4.74	0.00	42.88	0.00
524·1109	5.00	0.00	0.00	0.00	75.02
H = 0.3924	QRF:	0.9997	1.0001	1.0004	0.9999

I samamohs	Mammography rooms hs				
	Freq	I	II	III	IV
0	11.67	23.81	9.52	0.00	0.00
1·21	8.33	14.30	4.75	7.14	0.00
22·48	35.00	38.10	42.86	28.57	0.00
49·97	36.67	23.80	38.11	42.85	75.00
>97	8.33	0.00	4.76	21.44	25.00
H = 0.1729	QRF:	0.9999	1.0000	1.0001	1.0000

I saecohs	Ecography hs rooms				
	Freq	I	II	III	IV
1·99	51.67	71.44	66.70	14.21	0.00
100·264	31.67	19.04	28.56	57.19	24.99
265·579	11.67	9.52	4.75	28.61	0.00
>579	5.00	0.00	0.00	0.00	75.01
H = 0.3023	QRF:	0.9999	1.0002	0.9997	1.0000

I tachs	TAC hs				
	Freq	I	II	III	IV
0	33.33	71.48	23.76	0.00	0.00
1·49	11.67	9.52	23.83	0.00	0.00
50·126	21.67	9.51	33.37	28.54	0.00
127·252	26.67	9.49	19.03	71.46	0.00
>252	6.67	0.00	0.00	0.00	100.00
H = 0.5454	QRF:	1.0001	0.9996	1.0006	1.0001

I rmnhs	RMN hs				
	Freq	I	II	III	IV
0	71.67	95.26	85.72	35.66	0.00
36·117	11.67	0.00	9.52	35.74	0.00
118·334	15.00	4.74	4.76	28.60	75.00
>334	1.67	0.00	0.00	0.00	25.00
H = 0.3079	QRF:	0.9999	1.0001	0.9997	1.0003

I accelihs	Linear accelerator hs				
	Freq	I	II	III	IV
0	86.67	100.00	90.47	85.73	0.00
1·137	6.67	0.00	9.53	7.14	24.98
>137	6.67	0.00	0.00	7.12	75.02
H = 0.2191	QRF:	1.0000	1.0000	0.9997	1.0008

I etelechs	E. Telecobaltoteràpia hs				
	Freq	I	II	III	IV
0	86.67	95.24	90.48	85.71	24.96
1·90	10.00	4.76	4.76	7.14	75.04
>90	3.33	0.00	4.76	7.15	0.00
H = 0.1115	QRF:	0.9999	0.9999	0.9999	0.9999

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I simulahs	Simulators hs				
	Freq	I	II	III	IV
0	83.33	95.24	90.48	78.57	0.00
1·45	11.67	0.00	9.52	14.29	74.99
>45	5.00	4.76	0.00	7.14	25.01
H = 0.1851	QRF:	1.0000	1.0000	0.9998	1.0005

I eplanihs	E. Planning hs				
	Freq	I	II	III	IV
0	83.33	95.24	90.48	78.57	0.00
1·65	10.00	4.76	9.52	7.14	50.00
>65	6.67	0.00	0.00	14.29	50.00
H = 0.1867	QRF:	1.0000	1.0000	0.9998	1.0005

I gammahs	Gammacameras hs				
	Freq	I	II	III	IV
0	85.00	100.00	90.48	78.56	0.00
1·100	6.67	0.00	4.76	21.44	0.00
>100	8.33	0.00	4.75	0.00	100.00
H = 0.2719	QRF:	1.0000	0.9999	0.9999	1.0004

I ubraquhs	U. Braquitherapy hs				
	Freq	I	II	III	IV
0	91.67	100.00	90.47	100.00	24.96
1·50	5.00	0.00	9.53	0.00	25.01
>50	3.33	0.00	0.00	0.00	50.03
H = 0.1639	QRF:	1.0000	0.9999	1.0000	0.9996

I dopregn	Pregraduated teaching				
	Freq	I	II	III	IV
0	40.00	66.68	42.85	7.11	0.00
1·148	33.33	33.32	47.64	21.42	0.00
149·416	13.33	0.00	9.51	42.89	0.00
417·1334	10.00	0.00	0.00	28.58	50.00
>1334	3.33	0.00	0.00	0.00	50.00
H = 0.4583	QRF:	1.0002	0.9999	0.9999	1.0002

I doposgpl	Postgraduated teaching				
	Freq	I	II	III	IV
0	61.67	100.00	71.43	7.08	0.00
1·48	20.00	0.00	28.57	42.89	0.00
49·169	11.67	0.00	0.00	50.03	0.00
>169	6.67	0.00	0.00	0.00	100.00
H = 0.6332	QRF:	1.0003	1.0000	0.9998	1.0001

I dopotges	Special postgraduated teaching				
	Freq	I	II	III	IV
0	61.67	100.00	71.43	7.09	0.00
1·7	18.33	0.00	28.57	35.75	0.00
8·21	11.67	0.00	0.00	50.05	0.00
>21	8.33	0.00	0.00	7.12	100.00
H = 0.6038	QRF:	1.0003	1.0001	0.9995	1.0011

Table 3. Estimated values of $\lambda_{kjl.}$ for the 60 internal variables (cont)

I llirsnum	Beds				
	Freq	I	II	III	IV
0	76.67	100.00	90.50	35.66	24.97
1·6	21.67	0.00	9.50	64.34	50.02
>6	1.67	0.00	0.00	0.00	25.01
H = 0.2725	QRF:	1.0001	0.9999	0.9999	0.9996

I labrepa	In-vitro repropduction laboratory				
	Freq	I	II	III	IV
no	88.33	95.25	90.48	92.86	24.96
si	11.67	4.75	9.52	7.14	75.04
H = 0.0859	QRF:	0.9999	1.0000	1.0000	0.9996

I upolisep	U. Poltrauma i sèptics				
	Freq	I	II	III	IV
no	85.00	95.25	100.00	64.27	24.96
si	15.00	4.75	0.00	35.73	75.04
H = 0.1663	QRF:	0.9999	1.0002	0.9997	0.9997

I litotr	Litotriptor				
	Freq	I	II	III	IV
0	95.00	100.00	95.24	92.85	74.99
1·2	3.33	0.00	0.00	7.15	25.01
3	1.67	0.00	4.76	0.00	0.00
H = 0.0659	QRF:	1.0000	1.0000	0.9999	0.9997

Table 4. g_{ik} for each hospital.

	Pure type 1	**Pure type 2**	**Pure type 3**	**Pure type 4**	**Pure type 5**
1	1.0000	0.0000	0.0000	0.0000	0.0000
2	1.0000	0.0000	0.0000	0.0000	0.0000
3	0.1219	0.8781	0.0000	0.0000	0.0000
4	0.1074	0.8926	0.0000	0.0000	0.0000
5	1.0000	0.0000	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.8306	0.1694	0.0000
7	1.0000	0.0000	0.0000	0.0000	0.0000
8	0.0000	0.8979	0.1021	0.0000	0.0000
9	1.0000	0.0000	0.0000	0.0000	0.0000
10	0.4336	0.5664	0.0000	0.0000	0.0000
11	0.0000	0.0000	0.9117	0.0883	0.0000
12	0.0000	0.0000	0.8281	0.1719	0.0000
13	0.0000	0.0000	1.0000	0.0000	0.0000

14	0.0668	0.8541	0.0000	0.0749	0.0042
15	0.1311	0.8663	0.0000	0.0000	0.0026
16	0.0000	1.0000	0.0000	0.0000	0.0000
17	0.0000	1.0000	0.0000	0.0000	0.0000
18	1.0000	0.0000	0.0000	0.0000	0.0000
19	0.1763	0.8237	0.0000	0.0000	0.0000
20	1.0000	0.0000	0.0000	0.0000	0.0000
21	0.0004	0.0000	0.7114	0.2625	0.0257
22	0.0000	1.0000	0.0000	0.0000	0.0000
23	0.0000	1.0000	0.0000	0.0000	0.0000
24	0.0000	0.9690	0.0310	0.0000	0.0000
25	0.1904	0.8096	0.0000	0.0000	0.0000
26	0.0000	1.0000	0.0000	0.0000	0.0000
27	0.0000	0.0000	1.0000	0.0000	0.0000
28	0.0000	0.0000	0.8608	0.1392	0.0000
29	0.0000	0.0000	0.0000	0.0000	1.0000
30	0.0684	0.9316	0.0000	0.0000	0.0000
31	0.0011	0.9989	0.0000	0.0000	0.0000
32	0.0000	1.0000	0.0000	0.0000	0.0000
33	0.0000	0.0011	0.9989	0.0000	0.0000
34	0.0000	1.0000	0.0000	0.0000	0.0000
35	0.0000	0.0000	0.0000	1.0000	0.0000
36	1.0000	0.0000	0.0000	0.0000	0.0000
37	1.0000	0.0000	0.0000	0.0000	0.0000
38	1.0000	0.0000	0.0000	0.0000	0.0000
39	0.0000	1.0000	0.0000	0.0000	0.0000
40	0.0000	0.0000	1.0000	0.0000	0.0000
41	0.9193	0.0807	0.0000	0.0000	0.0000
42	0.0000	0.0000	1.0000	0.0000	0.0000
43	0.0000	0.0000	1.0000	0.0000	0.0000
44	0.0000	0.0000	0.0000	1.0000	0.0000
45	0.0000	0.1347	0.8653	0.0000	0.0000
46	0.0000	0.0000	1.0000	0.0000	0.0000
47	0.0000	0.0000	0.0000	1.0000	0.0000
48	1.0000	0.0000	0.0000	0.0000	0.0000

49	0.0273	0.8680	0.0732	0.0315	0.0000
50	0.2045	0.2122	0.5833	0.0000	0.0000
51	0.0000	0.8870	0.1127	0.0003	0.0000
52	0.0000	0.3956	0.6044	0.0000	0.0000
53	0.0765	0.0000	0.9235	0.0000	0.0000
54	0.0045	0.9955	0.0000	0.0000	0.0000
55	0.0000	0.0000	1.0000	0.0000	0.0000
56	0.0000	0.0000	0.0000	1.0000	0.0000
57	0.0000	0.0000	0.0000	0.0000	1.0000
58	0.0018	0.9756	0.0000	0.0226	0.0000
59	0.0000	0.0000	0.0000	0.0000	1.0000
60	0.0000	0.0000	0.0000	0.0000	1.0000

Table 5. Grade of membership distribution

						GOM Distribution					
Range	I	II	III	IV	V	Range	I	II	III	IV	V
<= 0.00%	33	32	39	47	53	50.0% to <52.5%	0	0	0	0	0
0.0% to < 2.5%	0	0	0	0	0	52.5% to <55.0%	0	0	0	0	0
2.5% to < 5.0%	4	1	0	2	2	55.0% to <57.5%	0	0	0	0	0
5.0% to < 7.5%	1	0	1	1	1	57.5% to <60.0%	0	1	0	0	0
7.5% to <10.0%	2	0	1	1	0	60.0% to <62.5%	0	0	1	0	0
10.0% to <12.5%	1	1	0	1	0	62.5% to <65.0%	0	0	1	0	0
12.5% to <15.0%	2	0	2	0	0	65.0% to <67.5%	0	0	0	0	0
15.0% to <17.5%	1	1	0	1	0	67.5% to <70.0%	0	0	0	0	0
17.5% to <20.0%	0	0	0	2	0	70.0% to <72.5%	0	0	0	0	0
20.0% to <22.5%	2	0	0	0	0	72.5% to <75.0%	0	0	1	0	0
22.5% to <25.0%	1	1	0	0	0	75.0% to <77.5%	0	0	0	0	0
25.0% to <27.5%	0	0	0	0	0	77.5% to <80.0%	0	0	0	0	0
27.5% to <30.0%	0	0	0	1	0	80.0% to <82.5%	0	0	0	0	0
30.0% to <32.5%	0	0	0	0	0	82.5% to <85.0%	0	2	0	0	0
32.5% to <35.0%	0	0	0	0	0	85.0% to <87.5%	0	0	2	0	0
35.0% to <37.5%	0	0	0	0	0	87.5% to <90.0%	0	3	2	0	0
37.5% to <40.0%	0	0	0	0	0	90.0% to <92.5%	0	4	0	0	0
40.0% to <42.5%	0	1	0	0	0	92.5% to <95.0%	1	0	2	0	0
42.5% to <45.0%	0	0	0	0	0	95.0% to <97.5%	0	1	0	0	0
45.0% to <47.5%	1	0	0	0	0	97.5% to <100.0%	0	1	0	0	0
47.5% to <50.0%	0	0	0	0	0	= 100.0% !	11	11	8	4	4