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Resource Use and Cost Heterogeneity in Swedish Geriatric Rehabilitation

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Contents

List of tables

Preface

Resource Use and Cost Heterogeneity in Swedish Geriatric Rehabilitation is a working paper within CEFOS research area 'Administrative and organizational aspects of the public sector'. Within this program Research Fellow Almas Heshmati is leading a project about productivity and efficiency in health care. *Resource Use and Cost Heterogeneity in Swedish Geriatric Rehabilitation* is the sixteenth working paper published by CEFOS.

In the paper the authors consider specification and estimation of production and cost functions in short term geriatric rehabilitation. For the producers to be able to estimate future revenues and to plan the resources needed considering hospital beds and staff, knowledge about a number of parameters, including the estimated length of stay, predicted Diagnosis Related Group (DRG) cost and total cost and also the different types of paramedical inputs during the stay, are crucial.

Göteborg, May 1997

Lars Strömberg
Director, CEFOS

Introduction[1]

Geriatric Medicine

Geriatric medicine is a rather recently established medical specialty. It was not until the early 20th century that the term geriatrics was coined by Nascher (1914). Geriatric medicine deals with the diseased elderly, who often have more than one disease present and are often functionally deficient. This is probably one of the reasons why the elderly so often are excluded in scientific studies, although the elderly, despite their relatively low proportion in the population, use a very large amount, about 1/4 of all hospital days, of the total resources of health care (Freiman and Murtaugh (1995)). Freiman and Murtaugh also showed that frail elderly, such as nursing home patients, used hospital stays 2.5 times more often than those not in nursing homes and that their length of stay was 56% longer. Particularly during the last year of life, the use of health care resources of the elderly is extremely high.

Due to the constrained budget to health care during the last decades, there has been an increasing need for cost models for health care services to the elderly. But ever since the development and implementation of the DRG system (see Fetter (1991) and Casas (1993)) as a payment model, first implemented in the U.S. but later tested in many other countries, its use for geriatric patients has been questioned, particularly as part of a prospective payment system.[2] The reasons for this are several: the elderly often have a longer and more variable length of stay in

[1] Financial support from the Center for Public Sector Research is gratefully acknowledged. We are grateful to Finn Forsund, Lars Strömberg, Lennart Hjalmarsson, Ann Veiderpass and other participants of the seminars at CEFOS and the Department of Economics, Göteborg University for helpful comments.

[2] See Cutler (1995), Pope (1990), and others.

acute care settings. They are also often discharged to other health care facilities for the elderly, such as nursing homes or residential homes with varying waiting lists. Another reason is that the DRG system only contains one group for rehabilitation, which is one of the major tasks for geriatric medicine world-wide and should be better differentiated in a descriptive or payment system. Therefore, a better grouping of patients according to rehabilitation needs and functional status would be needed to have also the elderly included in a true prospective payment system or cost model.

This need for a cost model, including care for the elderly with short lengths of stays for geriatric rehabilitation, was furthermore stressed after the so called Care of the Elderly Reform Act (Adel-reformen), in Sweden.[3] As of January 1, 1992, all long-staying nursing home patients were administratively transferred to the local community, while the short-term geriatric rehabilitation and acute care was kept within the county councils. This reform would have been a golden opportunity to develop intelligent cost models for medical care of the elderly. However, few attempts in this direction were made. Instead, in Stockholm county, an arbitrary modification of the DRG classification of the geriatric patients undergoing rehabilitation was established without field testing. This new system, including a subgrouping of the patients undergoing rehabilitation was followed by some extra data collection.

To be able to analyze the needs for hospital beds for short-term geriatric patients, as well as staff resources, a number of parameters needs to be known: the length of stay, depending on which DRG group, the foreseeable DRG cost and total cost (including costs pertained to outlier days during the stay) and also the paramedical input, such as minutes of physical therapists, occupational therapists and speech therapists during the stay. To check whether these parameters are predicted by the routinely collected data mentioned below, we have performed some statistical analyses. We have also included some extra data, not ordinarily

[3] For details on the Care of the Elderly Reform Act see Socialdepartementet (1989:27).

collected in Stockholm county. These data are from the Resource Utilization Groups, RUGs, a case-mix system originally developed in the U.S. to cover resource use in U.S. nursing homes, both geriatric rehabilitation, payed for by Medicare, but also long-staying nursing home residents. This system, now in its third version, RUG-III, is based on resource consumption per day and the case-mix index is related to an arbitrary value of 1.0.

Our hypothesis has been that the inclusion of the RUG variables in the regression models of the above parameters makes the results substantially better. The statistical approach enabled us to analyze the changes in geriatric care production and cost for individual departments during the implementation of a cost model in 1993 and 1994.

Patient Data, Collected Routinely

For many years, Stockholm county has been mandating patient data, initially (from the late 1960s) of in-patient care but in recent years including also out-patient care in hospitals and in primary health care. This standard data collection includes patient characteristics such as age and sex, admission and discharge dates, to which hospital, to which department and to which ward, if the admission was an emergency admission or not and from where the patient came. It also includes to where the patient is discharged, the length of stay in the department, the medical diagnoses and surgical procedures. From the early 1990's also the DRG group is calculated, as well as outlier days, and from 1993 a modified DRG system for geriatric patients is included.

This DRG modification divides geriatric rehabilitation patients into six categories in 1993 and three categories in 1994. During the fall of 1993 and 1994, respectively, a number of patients in departments of geriatric medicine in Stockholm county were assessed according to the RUG-III classification system to evaluate whether the modified classification could better differentiate the resource needs of different kinds of rehabilitation patients. (The results of these analyses are in preparation.) Data of more than 1700 patients undergoing geriatric rehabilitation were merged with data from the Stockholm county data base and analyzed in this paper. The six rehabilitation subgroups of 1993 were collapsed into the 1994 trichotomization.

This paper consider the short term geriatric rehabilitation. Standard production and cost function approaches are used to estimate production and cost models of four key parameters (DRG cost, total cost, length of stay and paramedical inputs) important to the elderly care. Collected DRG data from geriatric care in Stockholm County during 1993 and 1994 completed with individual resource use data are used for the statistical analyses. The objective is to find appropriate model specification for the short term geriatric rehabilitation. The models are aimed to be used in a prospective payment system. In order to analyze the sensitivity of the results, each of the four models are estimated using Cobb-Douglas and translog functional forms, patient or group level data and Stockholm Countys or a combination of the two data sets. Thus, this paper makes a significant contribution to the literature of geriatric rehabilitation considering model specification, estimation, testings and predictions.

The plan of this paper is as follows. In the next section the statistical models of production and cost functions are outlined. The geriatric data sets are described in a third section. The empirical results along with a comparison of different functional forms, data sets and data levels and the model performances are discussed in a forth section. Finally, in the fifth section summarizes and concludes this study.

The Statistical Models

In modeling the service production in short term geriatric rehabilitation we specify and estimate four different models, including total cost, DRG cost, paramedical services and length of stay. These models in specification, estimation and interpretation of results are very similar to the standard production and cost models. Thus, we approach modeling and estimating service production in geriatric medicine, both from the production and cost sides.[4] In the production function model, it is assumed that resources such as hospital beds, staff, etc. are given, and the objective of each department of geriatric medicine is to maximize outputs, which are number of bed days and paramedical services produced.[5] Special production characteristics are whenever available taken into account. In the cost function approach, the underlying assumption is that the output is exogenously given to a producer and each producer tries to minimize cost (DRG or total) in producing the given level of output(s). In the specification of the cost function models, we also consider patient characteristics. The costs are explained by output(s) and patient characteristics. No input prices enter the cost function. Variations in the main components of cost, i.e. average salaries and average rent per department, are estimated to be very small. Furthermore, all departments are subjected to the same prices when the purchases of material and other services are considered.

[4] The issues of analysis of cost and production in health care at aggregate hospital level are discussed in Buttler (1995), Wagstaff (1989), Grannemann et al. (1986), and others. More general discussion on the issues of the economics of health care are found in Johannesson (1996), Abbott (1995), McGuire et al. (1994), and Culyer (1991).

[5] Here we assume that maximum output by definition is the same as maximum capacity in terms of bed days a department can produce. In long term geriatric care the maximum capacity is very often attained. However, in short term geriatric rehabilitation for many reasons the capaicity utilization is often less than 100% and sometimes it also can exceed the full capacity. Disregarding levels of capacity, it is assumed that the care of the patients at different departments is of the same quality.

The Production Function Approach

We specify the service production function as

$$(1) \quad y_{it} = \beta_0 + \Sigma_j\beta_j x_{jit} + \Sigma_m\beta_m z_{mit} + ½(\Sigma_j\Sigma_k\beta_{jk}x_{jit}x_{kit} + \Sigma_m\Sigma_q\beta_{mq}z_{mit}z_{qit}) + \Sigma_j\Sigma_m\beta_{jm}x_{jit}z_m + \epsilon_{it},$$

where

$$(2) \quad \epsilon_{it} = \mu_i + u_{it},$$

$$i = 1, 2, ..., N, t = 1, 2, ..., T, j = 1, 2, ..., J, m = 1, 2, ..., M.$$

y_{it} is log of output for producer i in period t defined as either (i) the length of stay, or (ii) the paramedical inputs.[6] x is a vector of log of J inputs or resources. z is a M vector of department and patient characteristics including DRG group and time dummies. β is a vector of unknown parameters to be estimated. The error term, ϵ_{it} is composed of two components: a time-invariant department-specific effect, μ_i representing management;[7] and a random noise component, u_{it} representing unanticipated changes in various types of policy decisions over time affecting the geriatric care, etc.

The estimated values of the parameters (β and μ) can be used to analyze sensitivity of the results due to various model specifications. The β coefficients do not have any direct interpretation. The output elasticities are then calculated as the derivative of log output with respect to the log of each of the x-variables. The

[6] Ideally one should adjust the output measures for service quality differences. Quality adjusted measures of output can be obtained using various inputs and output quality indicators. Due to the lack of information on such indicators we were not able to perform any quality adjustment on output. However, we hope to be able to address this issue in near future. For details on modeling and adjustment of output for service quality with application to public schools, see Heshmati (1996). Also see Färe et al. (1995) for measurement of service quality of Swedish pharmacies.

[7] μ_i are unobserved department-specific effects not individual patient-specific effects. It is a group-specific effects based on the common characteristics of the group members, i.e. the health care department.

elasticities calculated show the effect of a percent change in the x-variables on the percentage change in output. The coefficients of z, on the other hand, show the effect of a change in the z-variables on the logarithm of output since all the z-variables are not measured in logarithms. The time dummy effect represent shifts in the production function compared to the base year of 1993. μ is a measure of individual producer effects. Thus, the β and μ parameters give some useful information about the technical aspect of the production of short term geriatric care.

A translog production function is chosen because it imposes minimum a priori restrictions on the underlying production technology and it approximates a wide variety of functional forms. The assumptions made about the error terms are as follows:(i) μ_i are fixed parameters to be estimated, (ii) u_{it} are independently and identically distributed with mean zero and constant variance ($u_{it} \sim$ i.i.d.$(0,\sigma^2_u)$), (iii) μ_i and u_{it} are independent, and finally (iv) μ_i and u_{it} are independent of x- and z-variables. The model can be estimated by the ordinary least squares (OLS) or the maximum likelihood estimation (MLE) methods. To avoid distributional assumption about u, we follow the OLS method.

In addition to the patient level data, described above, we also used an approach where instead of patient level, group level data are constructed. The groups are based on a combination of department, DRG subgroups and time periods. This approach is similar to the pseudo panel data approach suggested by Deaton (1985). The pseudo panels are created by grouping the individual observations into a number of homogenous cohorts, demarcated on the basis of their common observable time-invariant characteristics. In the analysis one uses the cohort means rather than the individual observations. Pseudo panels have a number of advantages over the genuine panel data. First, the complex data management and computational problems of large data sets are significantly reduced because of a sharp fall in the number of observations. Second, the cohort means are easily defined in terms of some common key characteristics. The pseudo level data is useful for policy implications and compensation issues. Third, for confidential unit level data, the cohort means are not confidential. The problems associated with reporting confidential information do not apply to pseudo panels. Fourth, unlike genuine panel data, the pseudo panel data do not suffer from attrition. Finally, by constructing pseudo panels the length of time period (T) a unit is observed is increased, especially when repeated cross-sectional data is available for a longer period. Large T is required for consistency of some parameter estimates. The main disadvantage of pseudo panels are the loss of within cohort variation. If the within cohort variation is larger and more important than the between cohort variations, the results obtained from the patient level and cohort levels will be inconsistent with each other.[8]

The service production function (1) and (2) assuming group level data is specified as

$$(3) \quad y_{gt} = \beta_0 + \Sigma_j \beta_j x_{jgt} + \Sigma_m \beta_m z_{mgt} + \tfrac{1}{2}(\Sigma_j \Sigma_k \beta_{jk} x_{jgt} x_{kgt} + \Sigma_m \Sigma_q \beta_{mq} z_{mgt} z_{qgt}) + \Sigma_j \Sigma_m \beta_{jm} x_{jgt} z_{mgt} + \mu_g + u_{gt},$$

$$g = 1, 2, \ldots, G,$$

where $y_{gt}=(\Sigma_i y_{it}/n_g)^* \sqrt{n_g}$ and $x_{jgt}=(\Sigma_i x_{jit}/n_g)^* \sqrt{n_g}$ are log of output and log of vector of inputs for group g in period t again defined as (i) the length of stay, or (ii) the paramedical inputs, n_g is the number of observations in cohort g. β, μ and u are defined as previously. z and the error components are transformed in the same manner as y and x.

[8] For another application of pseudo panel data models see Heshmati and Kumbhakar (1997).

The Cost Function Approach

The production function approach assumes that x- and z-variables are all exogenously given and outputs (number of bed days and paramedical services), are endogenous. A potential problem in this relation is that output is hardly a decision variable to a producer.[9] The producers have to provide care services to the citizens. Instead, producers take their bed days as exogenously given, subject to their capacity limits and provide their services with minimum cost. Thus, it is perhaps reasonable to assume that producers use inputs in such a way that the cost of providing services is minimized. So the choice variables are inputs rather than outputs and the objective is to minimize cost rather than maximize output.

With this objective in mind, we estimate a cost function. Assuming that panel data is available, the translog cost relationship is specified as[10]

$$(4) \quad c_{it} = \beta_0 + \Sigma_j \beta_j p_{jit} + \beta_y y_{it} + \Sigma_m \beta_m z_{mit} + \tfrac{1}{2}(\Sigma_j \Sigma_k \beta_{jk} p_{jit} p_{kit} + \beta_{yy} y^2_{it} + \Sigma_m \Sigma_q \beta_{mq} z_{mit} z_{qit}) + \Sigma_j \beta_{jy} p_{jit} y_{it} + \Sigma_j \Sigma_m \beta_{jm} p_{jit} z_{mit} + \Sigma_m \beta_{my} z_{mit} y_{it} + \eta_i + w_{it},$$

where c_{it} is the log of costs for the department i in period t, p is a J vector of the log of input prices, y is the log of output(s), defined as number of bed days and para-medical inputs. z is a M vector of patient and department characteristics, β are unknown parameters, η are fixed time-invariant department effects to be estimated, and w is random noise component.

We choose a translog cost function for the flexibility reasons as mentioned above.[11] The following homogeneity and symmetry restrictions are imposed

[9] The producers might be able to affect the level of output by extending the waiting time. We do not find such an incentive. The departments are compensated for services produced.

[10] The cost model is written for a single output case. However, it can be generalized to incorporate a multiple output case. If input prices are available, the cost model together with the cost shares can be estimated as a system.

[11] No price information was available. Thus, no p_j and its interactions with z_m and y are included in the cost model specification. Thus, β_j, β_{jk}, β_{jy} and β_{jm} are restricted to be zero (for a

$\Sigma_j\beta_j=1$, $\beta_{jk}=\beta_{kj}$, $\Sigma_j\beta_{jk}=0$ for all k, $\Sigma_j\beta_{jy}=0$. The assumptions made about the error terms are: (i) η_i are fixed parameters, (ii) w_{it} ~ i.i.d.$(0, \sigma^2_w)$, (iii) η_i and w_{it} are independent, and finally (iv) η_i and w_{it} are independent of p, y and z-variables. We apply OLS to estimate the cost models.

Similar to the production function case, the translog pseudo panel cost relationship is specified as

$$(5) \quad c_{gt} = \beta_0 + \Sigma_j\beta_j p_{jgt} + \beta_y y_{gt} + \Sigma_m\beta_m z_{mgt} + \tfrac{1}{2}(\Sigma_j\Sigma_k\beta_{jk}p_{jgt}p_{kgt} + \beta_{yy}y^2_{gt} + \Sigma_m\Sigma_q\beta_{mq}z_{mgt}z_{qgt}) + \Sigma_j\beta_{jy}p_{jgt}y_{gt} + \Sigma_j\Sigma_m\beta_{jm}p_{jgt}z_{mgt} + \Sigma_m\beta_{my}z_{mgt}y_{gt} + \eta_g + w_{gt},$$

where $c_{gt}=(\Sigma_i c_{it}/n_g)*\sqrt{n_g}$ and $p_{jgt}=(\Sigma_i p_{jit}/n_g)*\sqrt{n_g}$, $y_{gt}=(\Sigma_i y_{it}/n_g)*\sqrt{n_g}$, are the log of costs, prices and output(s) for the group g, β are unknown parameters, η and w are defined and transformed in the same way as c, p and y variables are.

similar case see Chu (1991) with application to post offices)). An alternative to the above model specification is to estimate a labor-requirement model (see Kumbhakar and Hjalmarsson (1995) with application to Social Insurance offices) in a multi-output framework. In this study the cost or amount of different types of labor used related to individual patients can not be distinguished.

The Data

The data used in this study consists of two parts. The first part is identical to the routinely collected data on short term geriatric rehabilitation in the Stockholm county. The variables included in this part are the patient's age, sex, length of stay, total cost, DRG cost, and DRG weight. The second part is related to the Resource Utilization Group, RUGs, developed to reflect resource use by geriatric patients. It is based on patients' resource consumption per day. The variables included in the second part are paramedical input (minutes of paramedical rehabilitation), patient dependency (an ADL index, consisting of dependency in eating, transfer, toileting, and bed mobility), resource use (measured as the RUG-III case-mix index) and nurse rehabilitation for individual patients. Thus, the sample of patients consisted of patients receiving short term geriatric rehabilitation in 18 geriatric departments located in the Stockholm county during a certain measurement week in 1993 and 1994, respectively. The total number of observations was 1891. The few deceased patients, outlier patients with length of stay longer than 200 days and observations with missing values on the costs were excluded from the data. The number of observations used in the regression analysis was 1754 (93% of total).

The variable DRG cost (DRGK) is defined as the fixed amount of money that the County Council, following an agreement, has decided to pay to the producers of care for each DRG. It should cover costs related to staff, rent, education of staff, meals to patients, laboratory tests, X-ray, etc.

The variable total cost (TOTK) is an aggregate of the DRG cost and the additional cost that the county has to compensate the hospital/provider of care for expenses when the patient stays longer than a pre-agreed length of stay, the outlier days. It also includes (very rare in geriatric medicine) the costs related to intensive care.

The variable length of stay (VTID) is defined as the length of stay from admission date to discharge date. As mentioned above we have excluded lengths of stay larger than 200 days in the regression analysis.[12]

The paramedical input variable (POST) is the summarized time/week of paramedical services (physiotherapists, occupational therapists, speech therapists) if any of these services were given more than 15 minutes during the assessment week. POST is measured in minutes.

The variable DRG weight (DRGV) is the relative cost or fee of an average hospital patient of 1.0. The relative DRG weight is multiplied by a sum of money, around 16.000 SEK to get the DRG cost. So a DRGV of 3.5 means a DRG cost of 56.000 SEK for one admission. If the patient stays longer than X days, then outlier money is added to the total cost. Thus, if the patient stays within a length of stay less than the decided outlier limit, then DRG cost is equal to total cost, if no extra charges for intensive care, etc.

The Resource use variable (RUG3) is the relative resource use/day of these geriatric patients, based on ADL (Activities of Daily Living), medical diagnoses and treatments, and paramedical services. A patient undergoing rehabilitation usually gets a higher RUG3 value than a patient that don't get rehabilitation, and a more ADL-dependent person gets a higher value than a less dependent. The RUG3 values so far are based on the U.S. time measurements on elderly nursing home residents and standardized to 1.0 in the original U.S. sample. In Ljunggren (1992) the Swedish time measurements of RUG-II was adjusted to the U.S. data and it was shown that adjusted Swedish measures were quite parallel to the U.S. in this respect.

The nurse rehabilitation variable (RNCO) is the number of times during the assessment week that the residents/patients get nurse rehabilitation under the supervision of a physiotherapist, occupational therapist, etc. or get rehabilitation by the ward staff for maintenance of level of ADL.

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[12] The sample minimum length of stay is 10 days.

The patient dependency variable (ADLS) is an index consisting of the patient's dependency in the ADLS of eating, toileting, transfer and bed mobility. It runs from 4 (totally independent in these four ADLS) to 18 (totally dependent).

All variables measured in SEK are transformed to the fixed 1994 prices using municipality cost price index. In addition to the above variables the age and sex of patients, a time dummy and a number of department and DRG group dummy variables are used in the analysis to capture the age, sex, time and unobserved department and DRG effects. A summary of the data and the correlation matrices are given in Table 1 and Table 2, respectively.

The Results

In analyzing the short term geriatric rehabilitation, the following four model formulations and estimations are considered.

The DRG Cost Model

In modeling the DRG cost, two types of Cost models are estimated. The first type models, are based on the patient level data, while the second types are based on the group level data. Each of the two types are specified both as a Cobb-Douglas (CD) and as translog functional forms. In order to evaluate the sufficiency of the routinely collected data or the significance of the additional RUG data all four models are further estimated (i) using only the Stockholm County data (SLL) as well as (ii) a combination of the two data sets (ALL). The parameter estimates of all the eight models are reported in Table 4.a. Within each group of models (patient levels or group levels) one can perform tests for selection of the most appropriate model specification.

In the specification of the DRG cost model we use the age of patients, length of stay, resource use, patient dependency and a time dummy variable.[13] The later is introduced to capture the time shift in the cost structure during the transition from 1993 to 1994. In the most general model (translog model) where information from both of the data sets are used, the coefficient of determination, R^2, is 0.0786.

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[13] The DRG cost, total cost, length of stay and paramedical service models were first estimated by including the sex of patients as an explanatory variable. In no model we found the coefficient of sex to be significant and subsequently the sex variable was excluded from all the model specifications.

Most of the parameter estimates are found to be statistically insignificant at any reasonable levels of significance. The low value of R^2 indicates that only 7.9% of the variation in the DRG cost is explained by the above mentioned variables. In the restricted CD model, all parameters (except for ADLS) are statistically significant att the 5% levels of significance. The R^2 value is very close to that of the translog, 0.0723. The same is true when the root mean squared error (RMSE) is considered. An F-test of a Cobb-Douglas vs. a translog form rejects the former in favour of a translog specification. Another test indicates that the interaction terms should be excluded while the square terms be retained. The F-values of all models are significant at the less than 1% levels of significance.[14]

The coefficients of the translog cost functions with the exception of the time dummy variable do not have any direct interpretation. Therefore we calculate the elasticities of DRG cost with respect to each explanatory variable and output.[15] Since cost, explanatory variables and output are all expressed in logarithms, the elasticities are simply obtained from the partial derivative of the cost function with respect to the appropriate p, z and output variables. The cost elasticity, E_m, measuring the responsiveness of DRG cost to a one percent change in the mth z variable, is given by

(6.a) $E_m = \partial vc_{it} / \partial z_{mit} = \beta_m + \Sigma_q \beta_{mq} z_{qit} + \beta_{my} y_{it}$,

when the patient level data is considered and

(6.b) $E_m = \partial vc_{gt} / \partial z_{mgt} = \beta_m + \Sigma_q \beta_{mq} z_{qgt} + \beta_{my} y_{gt}$,

when the group level data is considered.

The elasticity of DRG cost with respect to output, E_y, measuring the responsiveness of DRG cost to a percent increase in the output, is given by

[14] In the restricted model, with the exception of the intercept, all explanatory variables are restricted to be zero.

[15] Here output is defined as the patients length of stay measured in days.

$$E_y = \partial vc_{it} / \partial y_{it} = \beta_y + \beta_{yy} y_{it} + \Sigma_m \beta_{my} z_{mit}, \tag{7.a}$$

using the patient level data and

$$E_y = \partial vc_{gt} / \partial y_{gt} = \beta_y + \beta_{yy} y_{gt} + \Sigma_m \beta_{my} z_{mgt}, \tag{7.b}$$

using group level data.

The estimates of returns to scale (RTS), defined as the percentage change in output due to a proportional increase in the factor inputs, can be calculated as the reciprocal of output elasticity from the following relation

$$RTS = (1/E_y). \tag{8}$$

If the estimate of RTS is greater than, equal to, or less than one, the returns to scale is classified as increasing, constant, or decreasing. All cost and output elasticities vary both over time and across producers.

The calculated average cost elasticity with respect to age, E_{AGE}, is 0.12. E_{AGE} is inter-preted as an increase in the age of patients with 1% will result in an increase in the DRG cost with 0.12%. The DRG cost elasticity with respect to output, E_{VTID} is 0.06, interpreted as an increase in the length of stay with 1% will increase the DRG cost with 0.06%. The cost elasticity with respect to RUG3, E_{RUG3}, is 0.13. It is interpreted as an increase in the patient resource use per day with 1%, increases the DRG cost with 0.13%. The cost elasticity with respect to ADLS, E_{ADLS}, is 0.03 and not significant. The corresponding elasticities calculated using the CD form are 0.10, 0.06, 0.13 and -0.01, respectively. The E_{ADLS} elasticity has unexpectedly negative sign.

The models estimated based on the group levels data produces results which are difficult to interpret. All elasticities calculated are very high compared to the patient level models. The overall fit of the group level models in terms of R^2 seems to be much better in comparison to the patient level data. However, the RMSE are close to those of the patient level models. The high R^2 values can be explained by the fact that all within group variations are omitted following grouping the data.

It should be noted that these two types of models are non-nested. Thus, specification tests are not possible to perform. Three different measures proposed for assessing the predictive accuracy of general translog models in evaluating ex post forecasts of the DRG cost employed are: root mean squared error (RMSE), mean absolute error (MAE) and Theil U statistic (THLU).[16] RMSE and MAE are based on the residuals from the forecasts while THLU is related to R^2 but not bounded by zero and one. The THLU value is very low, 0.02, indicating a good forecasting performance.

The parameter estimates from the translog models using only the SLL and SLL combined with the RUG data sets, ALL, were used to predict the patient level DRG costs. The average current DRG cost (C_{curr}), predicted DRG cost (C_{pred}) and percent prediction errors (PE) for each department were calculated as

(9) $PE_{it} = ((C_{pred}-C_{curr})/C_{curr})*100,$

where a negative/positive percent prediction error indicates an underestimation/ overestimation of the DRG cost.

The results from various measures of elasticities and predictions are reported in Table 5.a. Looking at the mean DRG costs by departments we find as expected a lower percent prediction error in the group level models. In general, different data levels produce the same rankings in terms of percent prediction error. In most cases the models produce a negative prediction error indicating an under-estimation of cost. The models show to have the best performance in predicting the DRG cost at the department No 11337. The highest prediction errors are found in the cases of departments number 10339 and 11013 (negative) and 11334 (positive). The overall mean percent prediction errors in the group level models are -2.5 (SLL) and -1.7 (ALL). The corresponding percent prediction errors are -3.5 and -3.4 in the patient level translog models.

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[16] For details on the calculation of measures of accuracy of forecats see Greene (1993, pp 197-198). For inference on predictive ability see West (1996).

The Total Cost Model

We use the same types of cost models as the DRG cost models, presented in the previous subsection, to model the total cost. These models differ only by the functional form chosen (CD or translog), data levels (patient or group) and data sets (SLL or ALL). The total cost differs from the DRG cost only if the patient is an outlier patient and also by the costs associated with intensive care being taken into account. Other than this they are the same. Thus, differences between these two model specifications is only due to the frequency of outlier patients.[17] The parameter estimates and specification test values of the eight total cost models are reported in Table 4.b.

The total cost models are specified using the variables age, resource use, patient dependency, paramedical services, a time dummy, and length of stay. Thus, the right hand side of the total cost models, considering a combined data set, differs from the DRG cost model by only in the paramedical services being included as explanatory variable in the former specification. The R^2 of the patient level models is within 0.48-0.60. The F-values of all models are significant at the $p<0.01$ level of significance. The improvement in the fit of the models compared to the R^2 of the DRG cost models (0.03-0.08) is due to the importance of the outlier patients to the dependent variable, and the existence of a strong association between cost and ADLS, VTID and RUG3 variables. The additional POST explanatory variable, its square and interactions with the other explanatory variables are found to be statistically insignificant in all of the eight total cost models. The coefficients of the first order and squares of the remainder two RUG variables (RUG3 and ADLS) are statistically significant in all models. The differences in the R^2 and RMSE measures are large comparing the CD and translog specifications. However, the differences due to the additional RUG data set is very

[17] It should be noted that patients with length of stay exceeding 200 days were excluded from the sample.

small. An F-test indicates that the RUG variables should be included in the specification of the total cost model and a translog form is preferred to the CD form.

The calculated cost elasticity with respect to age, E_{AGE}, is 0.03. An increase in age of patient with 1% will result in an increase in the total cost with 0.03%. The total cost elasticity with respect to the primary output, E_{VTID}, is 0.43, interpreted as an increase in the length of stay with 1% will increase the total cost with 0.43%. The cost elasticity with respect to RUG3, E_{RUG3}, is 0.09 interpreted as an increase in the patient resource use per day with 1% increases the total cost with 0.09%. The cost elasticity with respect to ADLS, E_{ADLS} and the secondary output POST, E_{POST}, are 0.00, the later being insignificant. The corresponding elasticities calculated using the CD form are -0.08, 0.43, 0.09, -0.03 and 0.00. The E_{AGE} and E_{ADLS} elasticities are negative and show largest differences compared to the translog elasticities.

The total cost models estimated, based on the group level data again produces results which are difficult to interpret. Most of the elasticities calculated are very high compared to the patient level models. The overall fit of the group level models in terms of R^2 seems to be much better in comparison to those of the patient level data. However, the RMSE are close to those of the patient level models. This high R^2 and lower RMSE values are explained by the fact that all within group variations are omitted following grouping the data. The different measures proposed for assessing the predictive accuracy of general translog models in evaluating ex post forecast of the total cost, RMSE, MAE and THLU statistics are calculated. The THLU value is very low, 0.01, indicating a good forecasting performance.

The parameter estimates from the translog models using only the SLL and ALL data sets were used to predict the patient level total cost. The average current total cost, predicted total cost and percent prediction errors together with elasticities for each department are reported in Table 5.b. Looking at the mean total cost by departments we find as expected a lower percent prediction error in the group level models. Different data levels produce the same ranking in terms of percent prediction error. In most cases the models produce a negative prediction error or an underestimation of the total cost. The models show to have the best performance in predicting the total cost at the department No 11011 and 11334. The highest (negative) prediction errors are found in the cases of departments number 10339, 11014 and 11333. The overall mean percent prediction errors in the group level models are -1.1 (SLL) and -0.8 (ALL). The corresponding percent prediction errors are -3.8 and -3.7 in the patient level translog models.

The Length of Stay Model

Four types of production models similar to the DRG cost and total cost models are used in modeling the length of stay. The models differ by the functional form chosen and data sets. These four models are further estimated using the group level data. The parameter estimates and the values of the specification tests performed associated with the above models are reported in Table 4.c.

The length of stay models are specified using age, the four RUG variables (i.e. resource use, patient dependency, paramedical inputs, nurse rehabilitation), a time dummy, and a number of dummy variables representing the DRG subgroups. The F-values show that all models are significant at the $p<0.01$ level of significance. The R^2 of the models based on patient level data are within the interval 0.0270 to 0.1783. Contribution from the SLL data to the specification of the VTID model is very poor. The information is limited to the age of patient, a time dummy and the DRG subgroup dummy variables. Assuming a CD form only 2.7% of the variations in the VTID is explained by the age and the time dummy variables, both of which are highly significant. An extension of the CD to a translog form, the fit of the model improves, R^2 increases to 0.1403 and RMSE decreases. However, the two explanatory variable (age and time dummy) including the squared age and one of the DRG-subgroup dummy variables are insignificant.

Thus, improved explanatory power of the model is only due to the inclusion of DRG subgroup dummies. An F-test rejects the CD in the favour of the translog specification.

An introduction of the additional four RUG variables in the specification, i.e. using the ALL data set, improves the performance of the model from 0.0270 to 0.1403 in the CD and from 0.1046 to 0.1783 in the translog cases, respectively. Thus, an inclusion of the RUG variables improves substantially power of the model in explaining variations in the patients length of stay. It should be noted that the improvements are obtained through the DRG subgroup effects. All first order, squared and interaction terms (with the exception of POST) are found to be insignificant. F-tests performed reject the restricted forms, namely a CD with/without RUG variables, the DRG subgroup dummies, and an exclusion of the squares and interaction terms, in the favor of the most general translog model (for details see Table 4.c).

Estimation of the length of stay models, using the group level data, resulted in an deterioration of the fit of the model in the most restricted form. The age of patient and the time dummy variables are found to be irrelevant in explaining variations in the length of stay. The fit of the models improves as the models becomes more general by including more explanatory variables. However, the parameter estimates in terms of their sizes and signs are unreasonable and mostly insignificant.

The coefficients of the time dummy variable in all models are negative, indicating a decreasing length of stay over time. During the transition from 1993 to 1994, the average length of stay was reduced from 59 days to 52 days. The estimated reductions depending on the model specifications are within the interval 3.6 to 6.5 days.

The elasticity of length of stay with respect to the age of the patient, E_{AGE}, is large and negative. This is interpreted as the older patients receive a shorter period of rehabilitation. This can be due to the lower life expectancy rate and high mortality rate compared to the younger patients. The elasticity of VTID with respect to resource use variable, E_{RUG3}, is as expected positive. On the average E_{RUG3} is 0.01 with relatively large dispersion among the patients. This is interpreted as the resource intensive patients tend to stay for longer period. The mean ADLS elasticity, E_{ADLS}, is the largest among the RUG variables (0.25). The positive association between VTID and patient dependency was expected. A weaker positive relationship between VTID and the remaining two RUG variables, i.e. paramedical inputs (0.05) and the nurse rehabilitation (0.02) with large standard deviations is found. The CD elasticities with the exception of the E_{RUG3} are very close to those of the translog model. The mean elasticities calculated using the parameters from the group level data assuming a CD form with the exception of E_{RUG3} are very close. However, in the translog case the positive signs of E_{RUG3}, E_{ADLS} and E_{RNCO} has unexpectedly changed. In general they show to be subjected to high dispersion (see Table 5.c)

The measures of predictive accuracy, RMSE and MAE, show that the translog specification using patient level data is the preferred model specification. The low value of Theil U statistics also show the predictive performance of the models to be good. Again the parameter estimates from the translog models, using the SLL and ALL data sets, were utilized to predict the length of stay for individual patients. The mean current and predicted values of the length of stay together with the percent prediction errors for each department are reported in Table 5.c. The observed mean length of stay is 56 days. The corresponding predicted value calculated, assuming the translog parameter estimates using SLL and ALL data sets, are 46 and 47 days, respectively. Inclusion of the RUG variables in the specification of the translog model improves the predictive performance of the model. The impact is, however, very little. The two data sets result in the same ranking of departments in terms of prediction accuracy. In general, disregarding the type of data set used, the percent prediction errors are negative. The underestimation of length of stay is relatively high and lies within the interval -17.9% and -16.1%. The best (worst) predictions is obtained in the case of departments number 11013

(11011). The group level models show a better predictive performance. The sample average percent prediction error is only -1.9%.

The Paramedical Services Model

The paramedical services is the second type of observed homogenous services produced at the departments of geriatric medicine. Unlike the number of bed days the paramedical inputs is not a general measure, but a measure of recorded rehabilitation time use. Again eight production models are estimated. These are distinguished by the functional form, data sets and data levels.[18] The parameter estimates together with the specification test results are reported in Table 4.d.

In the specification of the paramedical service model, the age of patient, patient dependency, total cost, a time dummy, a number of department and DRG group dummy variables are used as explanatory variables.[19] The F-values, although low, show that all models are significant at the $p<0.01$ level. The R^2s are very low. Depending on the type of data used, it is within the interval 0.0408-0.1414 and 0.1568-0.4662. The SLL data variables (age and total cost) contribution to the explanation of the variation in the paramedical inputs is very little. All coefficients in the restricted CD including the one associated with the time dummy variable are highly significant. An extension of the model to a translog

[18] A total of 93 observations with zero values of paramedical services are excluded from the estimation procedure. In order to avoid selectivity bias, ideally one should apply a two step estimation procedure (probit in the first step and least square in the second step) or alternatively a tobit model. The frequency of zero paramedical inputs is very low, only 5.3%. Thus, a least square procedure did not differ much from a 2 step procedure indicating no selectivity problem.

[19] The paramedical service model ideally should be explained by the types of therapies. The type, number and educational level of therapists involved in each occasion is important to the quality of the service. No such information is available. Thus, we used the total cost as a proxy to the above mentioned variables.

form including the department specific and the DRG group effects increases the R^2 to 0.1414 and RMSE is decreased. The first order variables and 2 of the DRG group dummies are found to be insignificant. On the other hand, the second order, interaction variables and most of the department dummies are significantly different from zero.

The SLL and ALL models differ by the patient dependency variable. An inclusion of the ADLS variable as expected improves the fit of the model. However, the improvement is marginal. As in the SLL case, in ALL models the positive impact arises mainly from the department dummies. In general the remainder variables are unchanged considering their signs, sizes and significance. Specification tests based on the sum of squared residuals, RSS, show that an inclusion of the ADLS variable, department and DRG group dummies and a flexible functional form is the appropriate paramedical service model specification. In all tests, the restricted models are rejected in favour of the most general model, i.e. ALL/4.

All four models mentioned above were estimated based on the group level data. The magnitude of the parameter estimates associated with all explanatory variables other than the dummy variables are found to be unreasonable. The ADLS variable is found to be insignificant and its incorporation in the model specification deteriorates the fit of the model, R^2 decreases and RMSE increases. Again the explained part of the variations in the paramedical services are entirely explained by the department effects and one of the DRG group effects. Various specification tests indicates the translog model specification as the preferred model specification.

The coefficient of the time dummy variable in all patient level data models is positive and significant in three out of four cases, indicating a 7-9% increase in 1994 in the paramedical inputs compared to the reference year, 1993.

Two out of three DRG group dummies were found to have negative coefficients and were insignificant. Only DRG subgroup 462N is significant and positive, indicating that this group of patients obtains on average 23% more therapy than the reference group, DRG 462.[20] In the estimation of the department effects, department number 10011 is used as the reference. Only 2 out of 16 departments effects are insignificant. The effects are very much different in levels. Department number 10339 is the only unit which uses less therapy than the reference and is insignificant. The remainder effects varies in the interval 0.19 and 0.80. Department number 11013 (11335) is the most (least) therapy intensive geriatric department in the sample.

Elasticities of paramedical services with respect to each explanatory variable were calculated. These are reported in Table 5.d. The elasticity of paramedical services with respect to the age of patient, E_{AGE}, is -0.85 assuming a Cobb-Douglas functional form. The corresponding elasticity on average is -0.93 when a translog functional form is applied. In the later case the elasticities calculated vary by observation. The sample standard deviation of E_{AGE} is 0.52. A number of point elasticities are found to be positive. The elasticity with respect to the patient dependency, E_{ADLS}, is on average -0.11 with large standard deviation (0.16). In general a positive association between age, patient dependency and the para-medical therapy inputs is expected. Aged patients after a relatively short length of stay are often transferred to nursing homes. The elasticity with respect to the total cost, E_{TOTK}, is on average 0.25. As expected the elasticity is positive indicating a strong relationship between the amount of therapy and the total cost. The E_{TOTK} elasticity is much higher, 0.35, assuming a Cobb-Douglas functional form. The elasticities calculated based on the group level data are mainly of the same sign but very different in magnitude and difficult to interpret.

The measures of predictive performance, RMSE and MAE, show that the translog model using ALL data set is the adequate model specification among the alternative models. The Theil U statistics is on the average 0.16, within the interval 0.11 and 0.20. The relative high value indicates a poor predictive accuracy. The

[20] Here DRG 462 consists of patients not classified into the three subgroups, i.e. DRG 462L, 462M and 462N. The number of patient identified as DRG 462 are 193. These are used as reference group in the regression analysis to estimate the department heterogeneity effects.

average current and predicted values of the paramedical inputs, together with the percent prediction error for SLL and ALL data sets assuming a translog functional form, are calculated and the means by department are reported in Table 5.d. The observed overall mean paramedical input is 197 minutes with large dispersion (147 minutes) among the patients. The predicted values are estimated to be 153 minutes with smaller standard deviation (50). The average prediction error is -22.3% indicating an underestimation of the paramedical inputs. It is within the interval -11% to -34%. Inclusion of the additional RUG variables neither makes any changes in the predictive performance of the model nor changes the ranking of the departments. The predictive accuracy using the group level data as expected is high. The sample mean percent prediction error is only 3.2%.

Summary and Conclusions

Geriatric medicine is a recently established medical speciality providing health care services to the elderly. The care of elderly consumes a large proportion of the total health care resources. This paper consider the short term geriatric rehabilitation. Standard production and cost function approaches are used to estimate production and cost models of a number of key parameters important to the elderly care. The four models estimated are related to the DRG cost, total cost, length of stay and paramedical services. Routinely collected DRG data from geriatric care in Stockholm County during 1993 and 1994, where the patients are divided into three categories, are used for the statistical analyses. The data is completed with a supplementary data set from Resource Utilization Groups, covering individual resource use in geriatric rehabilitation. The two data sets are merged together to improve the results obtained in terms of specification of models and the models predictive performances. The objective is to find appropriate model specification for the short term geriatric rehabilitation. The models are aimed to be used in a prospective payment system. In order to analyze the sensitivity of the results, each of the four models are estimated using Cobb-Douglas and translog functional forms, patient or group level data and Stockholm Countys or a combination of the two data sets. The main findings are as follows.

Among the sample departments, we observe a large variation in all variables involved. The number of patients observed together with their average length of stay are considered as good approximations of the department service capacity or sizes. A negative relationship between the number of patients and their length of stay, as was expected, is not valid in all cases. The number of patients and their average stay during the period of this study are within the intervals 27-285 patients and 38-72 days, respectively. The mean age of patients varies in the interval 75-83, and it is negatively correlated with the length of stay. Old patients are transferred to nursing homes. Paramedical inputs and resource use are highly correlated with large variations among the different departments. Their correlations with the DRG weight is much lower. The highest correlation is found between DRG cost and the total cost variables. The DRG cost and total cost per day are within the intervals 1856-3644 and 2256-3851 SEK, respectively. The nurse rehabilitation is negatively correlated with the cost variables.

In calculation of the DRG cost, the outlier patients and costs associated with intensive care are not considered. The model was specified using age, length of stay, resource use, patient dependency and a time dummy variable. The sex of the patients was insignificant and excluded from all model specifications. A translog model based on a combination of the two data sets was found to be a good representation of the DRG cost model. The supplementary RUG variables were mostly insignificant, although they have a minor positive effect on the fit of the model. The explanatory power of the model improves with 9%. The models based on the group level data produces results which are difficult to interpret. In general the calculated elasticities are much higher than those based on the patient level data. The measures of predictive performance indicates a good forecasting performance. The mean prediction error is estimated to be -3.4%, indicating an underestimation of the DRG cost.

Unlike the DRG cost, the variable total cost includes the outlier patients with longer stay than expected following agreements. The specification differs from the DRG cost by the paramedical input added to the set of explanatory variables. A translog model based on the two data sets is found as the preferred model specification. The fit of the model is relatively high. About 60% of variations in the total cost is explained by the model. Inclusion of the RUG variables contributes to the improvement in the explanatory power of the model by 21%. The model based on the group level data show a better fit but the results obtained are difficult to interpret. Test of the predictive accuracy of the model show a good forecasting perfor mance. The mean prediction error is -3.7%, again indicating an underestimation the total cost.

The length of stay model is specified using age, resource use, patient dependency, paramedical input, nurse rehabilitation, a number of time and DRG subgroup dummy variables. The RUG data sets and the DRG dummy variables contribution to the model performance is crucial. The explanatory power of the translog model increases with 70% following inclusion of the additional RUG variables. Again we find the group level data inappropriate in modeling the length of stay. The measures of predictive accuracy show that the predictive performance of the models is relatively good. However, the prediction error calculated is on the average -16.1%. The large underestimation of the length of stay depends on the high frequency of outlier patients in the sample.

The paramedical input model is specified using age, patient dependency, total cost and a number of dummies representing time, department and DRG subgroup effects. The specification is very poor in explaining variations in the paramedical services. In the selected general translog model only 14% of the total variation is explained. The additional RUG variables improves a little the model performance. However, most part of the improvement, 320%, is generated following incorporation of the department effects. The measures of predictive performance find the model performance to be poor. The calculated prediction errors show a relatively large underestimation of the paramedical services. The mean is -22.3%. It varies a lot among the geriatric departments.

Geriatric care contains specific knowledge and not only deals with elderly with a certain diagnosis. It also has to take into account physical dependency, cognitive disturbances, etc. The art of geriatric rehabilitation, whether performed in a hospital or is home based, is growing, thus establishing a need for further analyses of episodes of care. DRGs have very little room here.

We believe future research should emphasis on the issues of improvements of the specification of the above four models in analyzing the short term geriatric rehabilitation. First, the improvements should account for quality variables as well as incorporate new input variables. An extension of the single output production function approach to a multiple output production function approach is important in analyzing care services. The output measures should be adjusted using different approaches for quality differences. Quality adjusted measures of output can be obtained using various input and output quality indicators. The adjusted and unadjusted measures can then be compared to quantify the significance of the quality of the services considering the prospective payment system. A second improvement will be developed by adding more relevant variables. The new variables help to model a theoretically consistent cost or production function and to improve the explanatory power of the model as well as the predictive accuracy of the models. The new information should contain prices as well as the production characteristics at the department levels. A decomposition of the DRG cost or total cost to the underlying cost components such as: doctors, nurses, other staff, X-ray, labs, drugs, food, transportation, rent, material, etc. is desirable. Among the department characteristic variables worth mentioning are: the level of education, experience and density of the different type of staff and an evaluation of the service quality by the patient, health improvement, etc. Third, a larger number of observations per department observed during several time periods is required to improve the stability of the parameter estimates and the prediction performance of the models. This paper is one of the first attempts to analyze geriatric data and it shows that it is feasible to continue along this track. Care of the elderly needs this knowledge which will enable us to allocate resources in a reasonable way.

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Table 1 Summary Statistics of the Geriatric Care Data.[a]

Variable	Definition	Mean	Std dev	Minimum	Maximum
A. Patient level data (N=1754):					
A.1 SLL data:					
VTID	Length of stay	55.79	38.70	10.00	200.00
TOTK	Total cost	125732.56	64688.44	26568.00	460873.00
DRGK	DRG cost	97982.49	24873.54	26568.00	132883.00
VKOS	Total cost/day	2877.99	1566.81	492.00	10539.92
DKOS	DRG cost/day	2623.81	1748.87	198.27	10539.92
AGE	Age	79.45	8.71	45.00	106.00
DRGV	DRG-weight	6.04	1.55	1.62	8.30
A.2 RUG data:					
POST	Paramedical input	186.44	149.89	1.00	1175.00
ADLS	Patient dependency	8.10	4.54	4.00	18.00
RUG3	Resource use	1.54	0.64	0.65	3.68
RNCO	Nurse rehabilitation	1.43	1.74	0.01	7.00
B. Group (combination of department+drg+year) level data (N=103):					
B.1 SLL data:					
VTID	Length of stay	53.24	20.07	23.57	109.60
TOTK	Total cost	120343.14	38359.30	55248.89	234150.43
DRGK	DRG cost	94635.94	23941.77	45786.00	128679.78
VKOS	Total cost/day	2897.87	665.49	1432.77	4776.13
DKOS	DRG cost/day	2666.38	776.74	874.35	4776.13
AGE	Age	79.09	3.77	67.00	88.29
DRGV	DRG-weight	5.83	1.46	2.85	8.03
B.2 RUG data:					
POST	Paramedical input	187.88	79.03	26.25	400.00
ADLS	Patient dependency	8.27	2.18	4.00	13.40
RUG3	Resource use	1.55	0.33	0.95	2.52
RNCO	Nurse rehabilitation	1.45	0.98	0.00	4.43

a Stockholm County (SLL), Resource utilization groups (RUG).

Table 2 Correlation Matrix, % is the p-values.

	YEAR	AGE	DRGV	RUG3	POST	VTID	VKOS	DKOS	ADLS	RNCO
A. Patient level data (N=1754):										
YEAR	1.00									
%	0.00									
AGE	0.02	1.00								
%	0.37	0.00								
DRGV	-0.06	-0.02	1.00							
%	0.01	0.52	0.00							
RUG3	0.03	-0.15	0.24	1.00						
%	0.28	0.00	0.00	0.00						
POST	0.03	-0.16	0.21	0.77	1.00					
%	0.16	0.00	0.00	0.00	0.00					
VTID	-0.09	-0.16	0.14	0.21	0.16	1.00				
%	0.00	0.00	0.00	0.00	0.00	0.00				
VKOS	-0.01	0.09	0.21	-0.08	-0.03	-0.57	1.00			
%	0.79	0.00	0.00	0.00	0.09	0.00	0.00			
DKOS	0.05	0.13	0.18	-0.10	-0.05	-0.71	0.96	1.00		
%	0.05	0.00	0.00	0.00	0.01	0.00	0.00	0.00		
ADLS	0.04	-0.01	0.08	0.30	-0.06	0.22	-0.16	-0.17	1.00	
%	0.11	0.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
RNCO	-0.01	-0.04	0.05	0.26	0.07	0.18	-0.15	-0.17	0.35	1.00
%	0.81	0.07	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B. Group level data (N=103):										
YEAR	1.00									
%	0.00									
AGE	0.06	1.00								
%	0.49	0.00								
DRGV	0.16	-0.02	1.00							
%	0.10	0.81	0.00							
RUG3	0.11	-0.22	0.53	1.00						
%	0.26	0.02	0.00	0.00						
POST	0.09	-0.25	0.47	0.88	1.00					
%	0.35	0.01	0.00	0.00	0.00					
VTID	-0.01	-0.17	0.43	0.36	0.33	1.00				
%	0.90	0.08	0.00	0.00	0.00	0.00				
VKOS	0.03	0.25	0.25	0.05	0.02	-0.49	1.00			
%	0.79	0.01	0.01	0.59	0.86	0.00	0.00			
DKOS	0.13	0.25	0.23	0.28	0.01	-0.64	0.96	1.00		
%	0.18	0.01	0.77	0.92	0.00	0.00	0.00	0.00		
ADLS	0.16	0.15	0.34	0.37	0.07	0.33	-0.04	-0.07	1.00	
%	0.10	0.12	0.00	0.00	0.47	0.00	0.63	0.50	0.00	
RNCO	0.07	-0.16	0.15	0.16	0.02	0.40	-0.29	-0.32	0.40	1.00
%	0.45	0.11	0.10	0.79	0.00	0.00	0.00	0.00	0.00	0.00

Table 3 Mean Values of the Key Variables by Producer, 1993-1994.

Department	N	AGE	VTID[b]	DRGK	DKOS	TOTK	VKOS	DRGV	RUG3	POST
A. Year 1993 (N=1030):										
10011	46	84	45	90400	2716	106659	2912	5.62	1.21	95
10301	68	80	54	99346	3093	135652	3385	6.18	1.65	211
10306	145	82	53	86879	2364	118419	2688	5.41	1.26	144
10333	63	78	61	101148	2484	134866	2802	6.29	1.60	182
10339	88	80	43	111063	3563	132710	3815	6.93	1.26	94
10349	121	79	65	107821	2539	141245	2853	6.70	1.73	252
11001	19	81	37	85818	2922	92058	3014	5.34	1.61	166
11002	26	80	51	99459	2567	130498	2902	6.21	1.69	218
11010	200	78	67	98585	2098	145864	2507	6.13	1.50	164
11011	33	76	66	82297	1919	133589	2396	5.12	1.54	205
11013	59	78	53	112402	3387	123070	3507	6.99	1.91	297
11014	44	82	56	107086	2744	141629	3055	6.67	1.51	185
11333	27	76	78	98245	2262	184826	2871	6.12	1.56	224
11334	15	80	52	76363	2577	118382	3025	4.76	1.99	228
11335	34	75	61	92591	2305	139048	2682	5.75	1.54	177
11337	42	78	78	87927	1759	136042	2213	5.44	1.74	202
Mean	.	79	59	98384	2556	133971	2886	6.12	1.53	182
Std dev	.	.	41	29855	1811	73041	1591	1.87	0.68	151
B. Year 1994 (N=724):										
10011	70	83	45	96802	2998	107311	3094	5.89	1.37	109
10301	56	79	44	94605	3432	105288	3534	5.75	1.76	247
10303	60	81	58	93977	2216	113943	2368	5.70	1.66	228
10306	89	82	52	97442	2539	114532	2677	5.93	1.46	161
10333	36	75	63	105622	2460	128859	2656	6.41	1.73	233
10339	28	83	34	98751	3896	105253	3966	6.02	1.40	156
10349	77	78	56	96056	2338	114613	2497	5.84	1.51	189
11001	8	83	41	94403	3506	102090	3583	5.76	1.23	104
11002	18	81	32	87303	3661	91949	3717	5.32	1.87	257
11010	85	81	57	98665	2549	119753	2768	5.99	1.54	227
11011	34	74	70	100389	1794	137967	2120	6.09	1.55	196
11013	36	79	42	98521	3029	100366	3056	6.00	1.71	236
11014	30	81	60	95951	2445	128931	2687	5.84	1.61	204
11333	10	78	55	95940	2561	125952	2809	5.85	1.43	238
11334	22	78	52	92623	2722	111520	2907	5.65	1.58	168
11335	22	73	43	101046	3175	101494	3180	6.16	1.67	163
11337	43	78	51	102447	2816	114576	2926	6.22	1.53	158
Mean	.	80	52	97411	2720	114012	2866	5.92	1.56	192
Std dev	.	.	34	15198	1653	48154	1533	0.92	0.59	148

b The length of stay, VTID, is truncated at 200 bed days.

Table 3 Continued

Department	N	AGE	VTID	DRGK	DKOS	TOTK	VKOS	DRGV	RUG3	POST
C. Years 1993 and 1994 (N=1754):										
10011	116	83	45	94264	2886	107052	3022	5.79	1.31	103
10301	124	79	49	97205	3246	121939	3453	5.99	1.70	227
10303[c]	60	81	58	93977	2216	113943	2368	5.70	1.66	228
10306	234	82	53	90897	2431	116941	2684	5.61	1.34	150
10333	99	77	62	102775	2475	132682	2749	6.33	1.65	201
10339	116	81	41	108091	3644	126082	3851	6.71	1.29	109
10349	198	79	61	103245	2461	130888	2715	6.37	1.64	227
11001	27	82	38	88361	3095	95030	3182	5.47	1.50	147
11002	44	81	43	94486	3015	114728	3235	5.85	1.76	234
11010	285	79	64	98609	2232	138076	2585	6.09	1.51	183
11011	67	75	68	91478	1856	135811	2256	5.61	1.55	200
11013	95	78	48	107142	3251	114466	3336	6.62	1.83	274
11014	74	81	57	102572	2623	136481	2906	6.33	1.55	192
11333	37	77	72	97622	2343	168914	2854	6.05	1.53	228
11334	37	79	52	86031	2663	114302	2955	5.29	1.75	193
11335	56	75	54	95913	2647	124294	2878	5.91	1.59	171
11337	85	78	64	95272	2293	125183	2574	5.83	1.63	180
Mean	.	79	56	97982	2624	125733	2878	6.04	1.54	186
Std dev	.	.	39	24875	1749	64688	1567	1.55	0.64	150
D. Percent changes from 1993 to 1994 (N=1754):										
10011	52.2	-1.4	-0.9	7.1	10.4	0.6	6.2	4.9	13.5	15.0
10301	-17.6	-0.8	-18.7	-4.8	11.0	-22.4	4.4	-7.0	6.9	17.0
10306	-38.6	-0.2	-2.5	12.2	7.4	-3.3	-0.4	9.7	15.3	11.6
10333	-42.9	-4.0	4.0	4.4	-1.0	-4.5	-5.2	2.0	8.2	28.2
10339	-68.2	4.7	-20.9	-11.1	9.3	-20.7	4.0	-13.2	11.3	66.3
10349	-36.4	-0.7	-13.6	-10.9	-7.9	-18.9	-12.5	-12.9	-12.6	-24.8
11001	-57.9	1.8	11.2	10.0	20.0	10.9	18.9	7.7	-24.0	-37.4
11002	-30.8	0.7	-36.5	-12.2	42.6	-29.5	28.1	-14.3	10.6	18.0
11010	-57.5	3.2	-14.6	0.1	21.5	-17.9	10.4	-2.2	2.9	38.1
11011	3.0	-2.5	6.5	22.0	-6.5	3.3	-11.5	18.9	0.7	-4.4
11013	-39.0	2.4	-20.5	-12.3	-10.6	-18.4	-12.9	-14.3	-10.8	-20.4
11014	-31.8	-1.6	7.0	-10.4	-10.9	-9.0	-12.0	-12.4	6.5	10.4
11333	-63.0	3.4	-29.0	-2.3	13.2	-31.9	-2.2	-4.4	-8.4	5.9
11334	46.7	-2.9	0.2	21.3	5.6	-5.8	-3.9	18.7	-20.9	-26.2
11335	-35.3	-2.8	-30.8	9.1	37.7	-27.0	18.6	7.1	8.0	-8.0
11337	2.4	-0.4	-34.4	16.5	60.1	-15.8	32.2	14.2	-12.3	-21.7
Mean	.	-0.1	-12.1	2.4	12.6	-13.1	3.9	0.2	-0.3	4.2
Std dev	.	.	15.9	12.1	20.1	12.4	14.1	11.9	12.6	27.3

c No observation on department No 10303 in 1993 is available.

Table 4.a OLS Parameter Estimates, DRG Cost Models. The Dependent Variable is DRGK.[d]

Level	Patient level				Group level			
Function	Cobb-Douglas		Translog		Cobb-Douglas		Translog	
Data/Model	SLL/1	ALL[e]/2	SLL/3	ALL/4	SLL/5	ALL/6	SLL/7	ALL/8
β_0	10.9219[a]	10.7197[a]	9.7508[c]	10.9826[c]	8.8514[a]	7.3859[a]	191.1394	208.5593
β_{TDUM}	0.0401[a]	0.0329[b]	0.0376[a]	0.0328[b]	0.1500[a]	0.1129[a]	0.1366[a]	0.0854[c]
β_{AGE}	0.0492	0.1038[c]	0.2815	-0.7591	0.2632	0.6413	-81.4932	-85.6571
β_{VTID}	0.0792[a]	0.0618[a]	0.4459	0.6416	0.3453[a]	0.2215[a]	-1.9128	-7.1542
β_{RUG3}	.	0.1278[a]	.	-0.3218	.	0.5221[a]	.	21.0748
β_{ADLS}	.	-0.0049	.	0.5536	.	0.0463	.	-2.7749
β_{AGE2}	.	.	-0.0349	0.2945	.	.	18.0137	17.6231
β_{VTID2}	.	.	-0.0698[a]	-0.0858[a]	.	.	-0.3710	0.8063[b]
β_{RUG32}	.	.	.	0.3234[a]	.	.	.	0.1660
β_{ADLS2}	.	.	.	-0.0981	.	.	.	0.0391
$\beta_{AGE \times VTID}$	.	.	-0.0231	-0.0718	.	.	0.8581	2.4437
$\beta_{AGE \times RUG3}$	.	.	.	0.1384	.	.	.	-4.9373
$\beta_{AGE \times ADLS}$	.	.	.	-0.0944	.	.	.	0.9228
$\beta_{VTID \times RUG3}$	.	.	.	-0.0063	.	.	.	0.8265[b]
$\beta_{VTID \times ADLS}$	.	.	.	0.0310	.	.	.	-0.2034
$\beta_{RUG3 \times ADLS}$	.	.	.	-0.1215[a]	.	.	.	-1.0262
R^2_{adj}	0.0344	0.0723	0.0365	0.0786	0.2391	0.3675	0.2435	0.4197
RMSE	0.2841	0.2784	0.2838	0.2775	0.2471	0.2253	0.2464	0.2158
F-value	21.81[a]	28.33[a]	12.07[a]	10.97[a]	11.69[a]	12.85[a]	6.47[a]	5.92[a]
F-test1	.	.	.	1.65	.	.	.	1.82[c]
F-test2	.	.	2.28[c]	2.19[b]	.	.	1.19	1.87[c]
OBS	1754	1754	1754	1754	103	103	103	103

d Significant at the less than 1% (a), 1%-5% (b), and 5%-10% (c) levels of significance.
e ALL is combination of Stockholm County (SLL) and Resource Utilization Group (RUG) data sets.

F-test1: ALL/4 and ALL/8 models, only interaction terms are restricted to be zero.
F-test2: SLL/3 and SLL/7 models, both squares and interaction terms are restricted to be zero.
F-test2: ALL/4 and ALL/8 models, both squares and interaction terms are restricted to be zero.

Table 4.b OLS Parameter Estimates, Total Cost Models. The Dependent Variable is TOTK.

Level	Patient level				Group level			
Function	Cobb-Douglas		Translog		Cobb-Douglas		Translog	
Data/Model	SLL/1	ALL/2	SLL/3	ALL/4	SLL/5	ALL/6	SLL/7	ALL/8
β_{0}	10.5513[a]	10.4167[a]	13.9844[a]	13.4173[b]	6.9410[a]	6.3940[a]	62.9195	66.5020
β_{TDUM}	-0.0548[a]	-0.0583[a]	-0.0402[a]	-0.0446[a]	-0.0076	-0.0227	-0.0108	-0.0262
β_{AGE}	-0.1231[b]	-0.0800	-0.9082	-1.7563	0.3895	0.5837[c]	-25.2258	-14.5383
β_{VTID}	0.4345[a]	0.4271[a]	-0.6199	-0.4502	0.7698[a]	0.7140[a]	0.6306	4.3503
β_{RUG3}	.	0.0923[a]	.	-0.9936	.	0.3250[c]	.	44.1670
β_{ADLS}	.	-0.0282[c]	.	1.5716[a]	.	-0.0034	.	-5.5296
β_{POST}	.	-0.0001	.	0.2260	.	-0.0400	.	-14.6994
β_{AGE2}	.	.	0.3636	0.7852	.	.	5.9687	-0.0592
β_{VTID2}	.	.	0.4944[a]	0.5239[a]	.	.	0.1374	0.2115
β_{RUG32}	.	.	.	0.3560[c]	.	.	.	2.0975
β_{ADLS2}	.	.	.	-0.1563[b]	.	.	.	-0.5540
β_{POST2}	.	.	.	0.0276	.	.	.	0.1427
$\beta_{AGExVTID}$	.	.	-0.1902[b]	-0.2229[b]	.	.	-0.0909	-0.9229
$\beta_{AGExRUG3}$	.	.	.	0.3818[c]	.	.	.	-9.6364
$\beta_{AGExADLS}$	.	.	.	-0.2773[b]	.	.	.	2.4964
$\beta_{AGExPOST}$	.	.	.	-0.0767	.	.	.	3.4587
$\beta_{VTIDxRUG3}$	.	.	.	-0.0633[c]	.	.	.	-0.3136
$\beta_{VTIDxADLS}$	.	.	.	-0.0295	.	.	.	-0.3397
$\beta_{VTIDxPOST}$	.	.	.	-0.0137	.	.	.	0.0895
$\beta_{RUG3xADLS}$	.	.	.	-0.1328	.	.	.	0.5775
$\beta_{RUG3xPOST}$	.	.	.	-0.0398	.	.	.	-0.5177
$\beta_{ADLSxPOST}$	.	.	.	0.0198	.	.	.	-0.6157
R^2_{adj}	0.4839	0.4916	0.5789	0.5953	0.7488	0.7659	0.7435	0.7745
RMSE	0.3062	0.3039	0.2766	0.2718	0.1588	0.1533	0.1604	0.1504
F-value	548.79[a]	283.53[a]	402.68[a]	122.86[a]	102.35[a]	56.61[a]	50.26[a]	17.68[a]
F-test1	.	.	.	3.52[a]	.	.	.	1.26
F-test2	.	.	132.69a	30.18[a]	.	.	0.31	1.24
OBS	1754	1754	1754	1754	103	103	103	103

F-test1: ALL/4 and ALL/8 models, only interaction terms are restricted to be zero.
F-test2: SLL/3 and SLL/7 models, both squares and interaction terms are restricted to be zero.
F-test2: ALL/4 and ALL/8 models, both squares and interaction terms are restricted to be zero.

Table 4.c OLS Parameter Estimates, Length of Stay Models. The Dependent Variable is VTID.

Level	Patient level				Group level			
Function	Cobb-Douglas		Translog		Cobb-Douglas		Translog	
Data/Model	SLL/1	ALL/2	SLL/3	ALL/4	SLL/5	ALL/6	SLL/7	ALL/8
β_0	7.7628^a	6.3679^a	-3.6864	3.6863	8.7686^a	6.5512^b	-238.3102	-230.8390
β_{TDUM}	-0.0866^a	-0.1093^a	-0.0266	-0.0604^c	0.0076	-0.0540	-0.0211	-0.0263
β_{AGE}	-0.8988^a	-0.7735^a	4.1457	1.9954	-1.1129	-0.8180	111.8102^c	59.4813
β_{RUG3}	.	0.1152^b	.	-0.4686	.	0.3977	.	-92.8983^c
β_{ADLS}	.	0.2709^a	.	-0.6574	.	0.2767	.	25.2968
β_{POST}	.	0.0547^b	.	-0.8730	.	0.0397	.	38.5927^c
β_{RNCO}	.	0.0214	.	-0.5639	.	0.0641	.	0.7219
β_{AGE2}	.	.	-1.1397	-0.9244	.	.	-25.8273^c	1.0939
β_{RUG32}	.	.	.	-0.0939	.	.	.	4.1975
β_{ADLS2}	.	.	.	-0.2670^c	.	.	.	1.3031
β_{POST2}	.	.	.	0.0368	.	.	.	1.8854^c
β_{RNCO2}	.	.	.	0.1680	.	.	.	0.0180
$\beta_{AGExRUG3}$	.	.	.	0.0378	.	.	.	26.7892^b
$\beta_{AGExADLS}$	.	.	.	0.2305	.	.	.	-8.2281^c
$\beta_{AGExPOST}$	.	.	.	0.1362	.	.	.	-11.5321^b
$\beta_{AGExRNCO}$	.	.	.	0.1227	.	.	.	0.3144
$\beta_{RUG3xADLS}$	.	.	.	0.0291	.	.	.	-3.7018
$\beta_{RUG3xPOST}$	.	.	.	0.0561	.	.	.	-3.6255
$\beta_{RUG3xRNCO}$	.	.	.	0.0090	.	.	.	1.5264^c
$\beta_{ADLSxPOST}$	.	.	.	0.0820	.	.	.	1.8597^c
$\beta_{ADLSxRNCO}$	.	.	.	-0.0023	.	.	.	-0.3510
$\beta_{POSTxRNCO}$	.	.	.	-0.0178	.	.	.	-0.3925
β_{462L}	.	.	0.0601	0.0884	.	.	0.1076	0.0304
β_{462M}	.	.	0.2168^a	0.2079^a	.	.	0.2267^b	0.1755
β_{462N}	.	.	0.5705^a	0.4884^a	.	.	0.5595^a	0.4734^a
R^2_{adj}	0.0270	0.1046	0.1403	0.1783	0.0026	0.1719	0.3415	0.4258
RMSE	0.6610	0.6341	0.6214	0.6075	0.3601	0.3281	0.2926	0.2733
F-value	25.37^a	35.13^a	48.69^a	16.85^a	1.13	4.53^a	9.82^a	4.15^a
F-test1	.	.	.	11.57^a	.	.	.	3.22^a
F-test2	.	.	.	9.70^a	.	.	.	3.36^a
F-test3	.	.	77.47^a	46.80^a	.	.	16.41^a	8.14^a
OBS	1754	1754	1754	1754	103	103	103	103

F-test1: ALL/4 and ALL/8 models, only interaction terms and DRG dummies are restricted to be zero.
F-test2: ALL/4 and ALL/8 models, squares, interaction terms and DRG dummies are restricted to be zero.
F-test3: SLL/3 and SLL/7 models, only squares and interaction terms are restricted to be zero.
F-test3: ALL/4 and ALL/8 models, only DRG dummies are restricted to be zero.

Table 4.d OLS Parameter Estimates, Paramedical Time-Use Models. The Dependent Variable is POST.

Level	Patient level				Group level			
Function	Cobb-Douglas		Translog		Cobb-Douglas		Translog	
Data/Model	SLL/1	ALL/2	SLL/3	ALL/4	SLL/5	ALL/6	SLL/7	ALL/8
β_0	4.9476[a]	4.8347[a]	-11.1306	-6.2455	9.2939[b]	8.8821[b]	-204.8192	-303.1770
β_{TDUM}	0.0846[b]	0.0945[b]	0.0698	0.0869[c]	0.1333	0.1389	-0.0127	0.0205
β_{AGE}	-0.8633[a]	-0.8516[a]	4.2897	2.8257	-2.2238[a]	-2.1508[b]	37.7347	81.4396
β_{ADLS}	.	-0.1184[a]	.	0.6355	.	-0.0629	.	-3.4706
β_{TOTK}	0.3228[a]	0.3474[a]	1.1931	0.8128	0.4721[a]	0.4911[a]	22.6665	23.6488
β_{AGE2}	.	.	-3.3674[b]	-2.9939[c]	.	.	0.3511	-10.8783
β_{ADLS2}	.	.	.	-0.2895	.	.	.	-0.1755
β_{TOTK2}	.	.	-0.3862[b]	-0.3630[c]	.	.	-0.6475	-0.6030
$\beta_{AGExADLS}$	.	.	.	-0.1366	.	.	.	2.7621
$\beta_{AGExTOTK}$	.	.	0.8126[b]	0.8227[b]	.	.	-3.5196	-3.5163
$\beta_{ADLSxTOTK}$	.	.	.	0.0356	.	.	.	-0.7222
μ_{10301}	.	.	0.6806[a]	0.6501[a]	.	.	0.7461[a]	0.7200[a]
μ_{10303}	.	.	0.7141[a]	0.6965[a]	.	.	0.8474[a]	0.8463[a]
μ_{10306}	.	.	0.2688[a]	0.2394[b]	.	.	0.3749[b]	0.3505[c]
μ_{10333}	.	.	0.5655[a]	0.5437[a]	.	.	0.3369[c]	0.3487[c]
μ_{10339}	.	.	-0.1236	-0.1376	.	.	-0.0254	-0.0469
μ_{10349}	.	.	0.6195[a]	0.5887[a]	.	.	0.6458[a]	0.6251[a]
μ_{11001}	.	.	0.3992[b]	0.4161[b]	.	.	0.1417	0.0936
μ_{11002}	.	.	0.7682[a]	0.7824[a]	.	.	0.8031[a]	0.7557[a]
μ_{11010}	.	.	0.3630[a]	0.3387[a]	.	.	0.5184[a]	0.4866[b]
μ_{11011}	.	.	0.2973[b]	0.2642[b]	.	.	0.4659[b]	0.4359[c]
μ_{11013}	.	.	0.8041[a]	0.7771[a]	.	.	0.7955[a]	0.7856[a]
μ_{11014}	.	.	0.5193[a]	0.4969[a]	.	.	0.5995[a]	0.5160[b]
μ_{11333}	.	.	0.4640[a]	0.4323[a]	.	.	0.5738[a]	0.5484[b]
μ_{11334}	.	.	0.7452[a]	0.7464[a]	.	.	0.6376[a]	0.6491[a]
μ_{11335}	.	.	0.2016	0.1942	.	.	0.1305	0.2213
μ_{11337}	.	.	0.4179[a]	0.4330[a]	.	.	0.5434[a]	0.5857[a]
β_{462L}	.	.	-0.0522	-0.0696	.	.	0.1198	0.0675
β_{462M}	.	.	-0.0199	-0.0241	.	.	0.3546[b]	0.2838
β_{462N}	.	.	0.2306[b]	0.2523[b]	.	.	0.6972[a]	0.7283[a]
R^2_{adj}	0.0408	0.0455	0.1414	0.1464	0.1568	0.1493	0.4762	0.4662
RMSE	0.8584	0.8563	0.8121	0.8097	0.4289	0.4308	0.3380	0.3413
F-value	24.53[a]	20.76[a]	11.939[a]	10.82[a]	7.32[a]	5.48[a]	4.71[a]	4.07[a]
F-test1	.	.	.	8.70[a]	.	.	.	3.50[a]
F-test2	.	.	9.83[a]	8.84[a]	.	.	3.74[a]	3.33[a]
F-test3	.	.	9.15[a]	11.04[a]	.	.	8.03[a]	7.93[a]
OBS	1661	1661	1661	1661	103	103	103	103

F-test1: ALL/4 and ALL/8 models, interaction terms, department and DRG dummies are restricted to be zero.
F-test2: ALL/4 and ALL/8 models, squares, interaction terms, department and DRG dummies are restricted to be zero.
F-test2: SLL/3 and SLL/7 models, squares and interaction terms are restricted to be zero.
F-test2: SLL/3 and SLL/7 models, only DRG dummies are restricted to be zero.
F-test3: ALL/4 and ALL/8 models, only DRG dummies are restricted to be zero.

Table 5.a Mean Percent Prediction Error, Current and Predicted Values of the DRG Cost (Translog) Models by Department.

Level	Patient level						Group level					
Data/Model		ALL/4	ALL/4	SLL/3	ALL/4	SLL/3		ALL/8	ALL/8	SLL/7	ALL/8	SLL/7
Department	N	C_{curr}	C_{pred}	C_{pred}	PE[f]	PE	N	C_{curr}	C_{pred}	C_{pred}	PE	PE
10011	116	94264	93134	94194	-1.2	-0.1	7	93956	97511	91491	3.8	-2.6
10301	124	97205	94762	92810	-2.5	-4.5	7	94881	96381	88203	1.6	-7.0
10303	60	93977	98805	97491	5.1	3.7	3	101279	110760	108965	9.4	7.6
10306	234	90897	92770	94556	2.1	4.0	7	94498	89861	94709	-4.9	0.2
10333	99	102775	95501	94935	-7.1	-7.6	7	93491	92583	90500	-1.0	-3.2
10339	116	108091	90660	91994	-16.1	-14.9	7	94649	79499	81374	-16.0	-14.0
10349	198	103245	96452	95243	-6.6	-7.7	7	94281	91480	91247	-3.0	-3.2
11001	27	88361	91104	91640	3.1	3.7	4	89475	85649	84746	-4.3	-5.3
11002	44	94486	95546	92902	1.1	-1.7	5	95875	89435	86666	-6.7	-9.6
11010	285	98609	94755	95127	-3.9	-3.5	7	93945	93070	95141	-0.9	1.3
11011	67	91478	95897	96473	4.8	5.5	6	91646	94665	99653	3.3	8.7
11013	95	107142	96784	93592	-9.7	-12.6	6	102881	96227	87923	-6.5	-14.5
11014	74	102572	95517	95021	-6.9	-7.4	6	101469	99437	100456	-2.0	-1.0
11333	37	97622	94314	94412	-3.4	-3.3	5	87195	87140	94941	-0.1	8.9
11334	37	86031	95958	94380	11.5	9.7	6	91896	98004	93642	6.6	1.9
11335	56	95913	94631	93696	-1.3	-2.3	7	92453	85898	90404	-7.1	-2.2
11337	85	95272	95565	93389	0.3	0.5	6	96332	101854	96019	5.7	-0.3
Mean	.	97982	94685	94501	-3.4	-3.5	.	94636	93037	92248	-1.7	-2.5
Std dev	.	24873	7958	5312	.	.	.	23942	18308	13533	.	.

	Cobb-Douglas, ALL/2	Translog, ALL/4				Cobb-Douglas ALL/6	Translog ALL/8			
	CD	Mean	Std	Min	Max	CD	Mean	Std	Min	Max
Measures of predictive accuracy:[g]										
RMSE	.	0.28	0.06	0.15	0.39	.	0.20	0.07	0.10	0.35
MAE	.	0.22	0.04	0.13	0.28	.	0.15	0.05	0.08	0.28
THLU	.	0.02	0.01	0.01	0.03	.	0.02	0.01	0.01	0.03
Elasticities:										
E_{AGE}	0.10	0.12	0.09	-0.23	0.37	0.64	0.75	1.48	-3.39	4.75
E_{VTID}	0.06	0.06	0.06	-0.08	0.22	0.22	0.29	0.31	-0.63	0.84
E_{RUG3}	0.13	0.13	0.14	-0.13	0.42	0.52	0.53	0.46	-0.64	1.75
E_{ADLS}	-0.01	0.03	0.09	-0.18	0.23	0.05	0.12	0.27	-0.42	0.81

f Percent prediction error (PE).
g Root Mean squared error (RMSE), Mean absolute error (MAE) and Theil U statistic (THLU).

Table 5.b Mean Percent Prediction Error, Current and the Predicted Values of the Total Cost (Translog) Models by Department.

Level		Patient level						Group level				
Data/Model		ALL/4	ALL/4	SLL/3	ALL/4	SLL/3		ALL/8	ALL/8	SLL/7	ALL/8	SLL/7
Department	N	C_{curr}	C_{pred}	C_{pred}	PE	PE	N	C_{curr}	C_{pred}	C_{pred}	PE	PE
10011	116	107052	104571	106560	-2.3	-0.5	7	107131	108440	107709	1.2	0.5
10301	124	121939	117018	115838	-4.0	-5.0	7	114600	111106	106883	-3.0	-6.7
10303	60	113943	119548	119051	4.9	4.5	3	129837	135911	145887	4.7	12.4
10306	234	116941	115099	115990	-1.6	-0.8	7	119560	118511	120714	-0.9	1.0
10333	99	132682	126651	128129	-4.5	-3.4	7	114169	121963	119732	6.8	4.9
10339	116	126082	103743	104463	-17.7	-17.1	7	108492	91759	92806	-15.4	-14.5
10349	198	130888	128969	126897	-1.5	-3.0	7	115451	119054	119480	3.1	3.5
11001	27	95030	100193	100659	5.4	5.9	4	96614	100506	101056	4.0	4.6
11002	44	114728	108401	106120	-5.5	-7.5	5	117986	109388	105078	-7.3	-10.9
11010	285	138076	132180	131573	-4.3	-4.7	7	123924	126683	128386	2.2	3.6
11011	67	135811	136285	135457	0.3	-0.3	6	129588	138363	137003	6.8	5.7
11013	95	114466	113339	111747	-1.0	-2.4	6	107457	107403	102274	-0.0	-4.8
11014	74	136481	122166	122164	-10.5	-10.5	6	146096	140601	139259	-3.8	-4.7
11333	57	168914	150402	146064	-10.9	-13.5	5	140629	131959	134202	-6.2	-4.6
11334	37	114302	115173	114864	0.8	0.5	6	125152	127745	125640	2.1	0.4
11335	56	124294	119973	119958	-3.5	-3.5	7	125669	118576	120110	-5.6	-4.4
11337	85	125183	128108	130861	2.3	4.5	6	128929	131055	131528	1.6	2.0
Mean	.	125733	121080	120895	-3.7	-3.8	.	120343	119419	119060	-0.8	-1.1
Std dev	.	64688	49707	49117	.	.	.	38359	35788	34434	.	.

	Cobb-Douglas, ALL/2	Translog ALL/4				Cobb-Douglas, ALL/6	Translog ALL/8			
	CD	Mean	Std	Min	Max	CD	Mean	Std	Min	Max
Measures of predictive accuracy:										
RMSE	.	0.27	0.04	0.17	0.32	.	0.13	0.05	0.06	0.23
MAE	.	0.22	0.04	0.14	0.27	.	0.10	0.04	0.05	0.21
THLU	.	0.02	0.00	0.01	0.03	.	0.01	0.00	0.00	0.02
Elasticities:										
E_{AGE}	-0.08	0.03	0.24	-0.90	0.67	0.58	0.52	0.93	-2.77	3.28
E_{VTID}	0.43	0.42	0.34	-0.42	1.28	0.71	0.76	0.13	0.41	1.09
E_{RUG3}	0.09	0.09	0.14	-0.34	0.42	0.33	0.25	0.58	-0.88	1.96
E_{ADLS}	-0.03	-0.00	0.13	-0.29	0.31	-0.00	-0.02	0.33	-0.69	0.87
E_{POST}	-0.00	0.00	0.02	-0.08	0.08	-0.04	0.00	0.24	-0.64	0.56

Table 5.c Mean Percent Prediction Error, Current and Predicted Values of the Length of Stay (Translog) Models by Department.

Level		Patient level					Group level					
Data/Model		ALL/4	ALL/4	SLL/3	ALL/4	SLL/3		ALL/8	ALL/8	SLL/7	ALL/8	SLL/7
Department	N	V_{curr}	V_{pred}	V_{pred}	PE	PE	N	V_{curr}	V_{pred}	V_{pred}	PE	PE
10011	116	45	44	43	-2.8	-5.5	7	45	45	48	0.1	6.1
10301	124	49	46	45	-7.1	-8.2	7	46	50	52	7.0	11.0
10303	60	58	43	41	-25.2	-29.5	3	68	57	52	-16.2	-24.4
10306	234	53	42	43	-19.7	-18.5	7	53	48	50	-10.1	-6.1
10333	99	62	52	50	-15.5	-18.4	7	54	51	52	-5.9	-4.4
10339	116	41	47	48	13.7	16.4	7	38	47	50	25.9	33.4
10349	198	61	48	49	-21.2	-20.8	7	54	52	53	-3.1	-2.8
11001	27	38	45	44	19.7	16.2	4	42	48	47	14.9	12.4
11002	44	43	46	43	6.1	-1.0	5	45	52	49	15.4	9.7
11010	285	64	48	47	-25.7	-26.5	7	59	55	52	-6.9	-11.7
11011	67	68	46	47	-32.9	-30.8	6	65	56	52	-13.4	-19.7
11013	95	48	49	49	0.6	1.8	6	44	48	54	10.1	22.7
11014	74	57	45	45	-21.3	-21.6	6	64	55	52	-14.6	-18.4
11333	37	72	49	49	-31.1	-31.6	5	63	58	49	-6.8	-22.0
11334	37	52	44	41	-14.6	-20.6	6	57	50	52	-12.1	-8.9
11335	56	54	52	49	-3.5	-9.2	7	55	58	52	6.3	-6.2
11337	85	64	50	48	-21.9	-25.2	6	61	53	54	-13.4	-11.6
Mean	.	56	47	46	-16.1	-17.9	.	53	52	51	-1.9	-3.8
Std dev	.	39	14	12	.	.	.	20	15	12	.	.

	Cobb-Douglas, ALL/2	Translog, ALL/4				Cobb-Douglas, ALL/6	Translog, ALL/8			
	CD	Mean	Std	Min	Max	CD	Mean	Std	Min	Max
Measures of predictive accuracy:										
RMSE	.	0.60	0.06	0.52	0.76	.	0.24	0.06	0.14	0.38
MAE	.	0.49	0.06	0.42	0.62	.	0.19	0.06	0.12	0.34
THLU	.	0.16	0.02	0.13	0.19	.	0.06	0.02	0.04	0.10
Elasticities:										
E_{AGE}	-0.77	-0.79	0.23	-1.53	0.01	-0.82	-0.82	2.32	-6.43	9.95
E_{RUG3}	0.12	0.01	0.04	-0.16	0.12	0.40	-0.11	2.04	-5.53	6.12
E_{ADLS}	0.27	0.25	0.17	-0.24	0.57	0.28	-0.01	0.58	-2.21	1.29
E_{POST}	0.05	0.07	0.07	-0.14	0.26	0.04	0.16	0.70	-2.21	1.87
E_{RNCO}	0.02	0.04	0.07	-0.18	0.23	0.06	-0.01	0.16	-0.45	0.46

Table 5.d Mean Percent Prediction Error, Current and Predicted Values of the Paramedical Inputs (Translog) Models by Department.

Level		Patient level					Group level					
		ALL/4	ALL/4	SLL/3	ALL/4	SLL/3		ALL/8	ALL/8	SLL/7	ALL/8	SLL/7
Department	N	P_{curr}	P_{pred}	P_{pred}	PE	PE	N	P_{curr}	P_{pred}	P_{pred}	PE	PE
10011	96	125	91	91	-27.2	-27.2	7	108	106	106	-2.0	-1.9
10301	121	233	188	188	-19.2	-19.3	7	239	236	235	-1.5	-1.8
10303	58	236	188	188	-20.5	-20.5	3	250	245	246	-1.9	-1.5
10306	227	155	120	120	-22.6	-22.7	7	154	151	151	-1.5	-1.7
10333	91	218	185	183	-15.5	-16.1	7	174	165	164	-4.6	-5.3
10339	107	118	87	87	-26.2	-26.4	7	113	107	107	-4.8	-5.1
10349	192	235	189	189	-19.3	-19.6	7	214	214	213	-0.2	-0.5
11001	26	153	136	134	-11.1	-12.3	4	125	120	119	-4.3	-4.5
11002	43	239	196	195	-17.8	-18.5	5	235	234	234	-0.4	-0.5
11010	273	191	140	140	-26.5	-26.5	7	189	181	181	-4.4	-4.3
11011	66	203	136	136	-33.1	-33.1	6	199	195	195	-2.3	-2.4
11013	94	277	227	227	-18.1	-18.0	6	266	269	268	1.1	0.8
11014	65	219	164	163	-25.1	-25.5	6	207	188	188	-8.8	-9.2
11333	35	241	159	158	-34.1	-34.3	5	194	182	182	-6.1	-6.2
11334	31	230	200	198	-13.2	-14.0	6	219	212	210	-2.9	-4.1
11335	51	188	126	126	-33.1	-32.9	7	151	137	136	-9.7	-9.9
11337	85	180	154	154	-14.5	-14.6	6	203	196	199	-3.7	-2.0
Mean	.	197	153	153	-22.3	-22.3	.	188	182	182	-3.2	-3.2
Std dev	.	147	52	50	.	.	.	79	65	64	.	.

	Cobb-Douglas, ALL/2	Translog, ALL/4				Cobb-Douglas, ALL/6	Translog, ALL/8			
	CD	Mean	Std	Min	Max	CD	Mean	Std	Min	Max
Measures of predictive accuracy:										
RMSE	.	0.80	0.14	0.54	1.02	.	0.29	0.11	0.11	0.46
MAE	.	0.61	0.11	0.43	0.79	.	0.22	0.08	0.09	0.38
THLU	.	0.16	0.03	0.11	0.20	.	0.06	0.05	0.02	0.09
Elasticities:										
E_{AGE}	-0.85	-0.93	0.52	-2.58	1.21	-2.15	-1.32	1.13	-4.04	1.68
E_{ADLS}	-0.12	-0.11	0.16	-0.43	0.14	-0.06	-0.18	0.29	-0.82	0.31
E_{TOTK}	0.35	0.25	0.19	-0.49	0.89	0.49	-0.24	0.37	-0.94	0.76

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