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How does accounting for patient characteristics affect comparison of costs across hospitals?

By

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1. Abstract

Objectives:
Hospital costs are driven partly by the complexity of patients treated and partly by efforts to ensure cost control the latter being unobserved. We explore what effect controlling for different patient characteristics has on inferences drawn about what effort hospitals exert in cost control.

Methods:
We estimate fixed effects models in which (n=3,953) patients are clustered within six Danish vascular departments. We compare models including risk adjusters such as age, gender and a case-mix adjustment with models including health related characteristics such as smoking status, diabetes, ASA-score and socioeconomic characteristics such as income, employment and living alone.

Results:
The case-mix factor is an important explanatory factor and its inclusion changes the ranking of departments in terms of their effort. Adding health related variables only slightly changes the results of the comparisons across departments, and it does not alter the ranking of the departments. Differences in profiles of the patients between departments may partly explain the observed differences in departmental effects.

Conclusions:
Adding health related or socioeconomic patient characteristics only slightly improves our model in terms of explanatory power or when drawing inferences about the relative performance of vascular departments. This suggests that robust conclusions can be drawn about departmental efforts in controlling costs for vascular patients taking account only of the age, gender and case-mix of patients.

Keywords: Risk adjustment, hospital costs, panel data

2. Introduction

In the health care sector risk adjustment has traditionally been applied in a wide number of areas such as health insurance, capitation funding, provider payments and performance assessments. Some individuals or populations face higher risks of developing health problems earlier or more often than others due to diverse reasons such as genetics, behaviour (e.g. smoking), socioeconomic status and environmental milieu (1). Most often individuals or populations are not randomly distributed and as such may cause unfair comparisons across health care providers or create incentives for either health care providers or for health care purchasers (e.g. insurers) to avoid patients with higher risks of developing health problems or to suffer some kind of complication. These problems are the reason why risk adjustment is applied, the purpose being to determine the influence of individual's characteristics on costs or outcomes, and to account for these differences in order to calculate fair payment rates or to make fair comparisons of performance.

An extensive part of the literature about risk adjustment has arisen from handling problems with risk selection for health insurance purposes such as in the United States. Van der Ven and Ellis (2000) define risk adjustment as the use of information to calculate the expected health expenditures of individuals over a fixed period of time to determine payment rates for health insurers (2). These calculations may be used to predict costs for an individual, such as in calculating insurance premiums, or at a population level, such as when determining capitation payments to purchasing bodies. However, risk adjustment is also crucial in performance measurements as it is required in order to make fair comparisons of provider performance, whether providers are health care organisations (e.g. hospitals) or individuals (e.g. surgeons), in recognition that there are likely to be systematic differences in the types of patients these organisations or individuals care for.

Risk adjustment involves taking account of patient characteristics that explain costs or outcomes, over and above features of insurance scheme to which the patients belongs or of the provider from whom they receive treatment. For example, suppose one hospital routinely treats a higher proportion of elderly patients than another hospital, we would expect costs to be higher in the former hospital as, all else equal, costs are higher in organisations that treat a higher proportion of elderly patients (2-6). Costs may also be higher in organisations that systematically treat patients who display behaviours (such as smoking) that might give rise to more health complications or slower recovery times (7;8), and in organisations that serve more deprived populations (9;10). But costs may also differ between these two hospitals because one is more efficient than the other. It would be necessary to control for differences in the characteristics of patients before a judgement can be made about the relative efficiency of the two hospitals. The analytical challenge is that there are many potential patient characteristics that might influence costs (or outcomes). The purpose of risk adjustment is to identify and quantify the influence of these characteristics.

If risk adjustment is inadequate, e.g. if relevant patient characteristics are not taken account of, then differences may wrongly be interpreted as differences in performance. Moreover, if risk adjustment is inadequate comparison of costs or outcome data across hospitals may also create unintentional behavioural incentives. A well-known example of adverse behaviour was that of risk selection following the publication of mortality rates following coronary artery by-pass (CABG) by hospital and surgeon by the New York State Department of Health in 1989. The mortality rate declined following publication, but there were reports of cardiac surgeons turning away the sickest and most severely ill patients in order to avoid poor outcomes and hence poor public rating (11). A higher number of patients were transferred to hospitals outside New York after the introduction of the public report cards, and these patients generally had higher risk profiles than patients transferred to the same hospitals from other states (12). The introduction of the public report cards had an impact on the racial disparities in the use of CABG, suggesting that surgeons avoid patients perceived to be at higher risk for bad outcomes, such as blacks and Hispanics (11).

In this paper we consider what risk adjustment should be undertaken when comparing costs across hospital departments specialising in the treatment of patients suffering vascular conditions. We explore whether we will be more precise in the estimation of departmental performance when extending the number of patient characteristics from those routinely collected such as age, gender and a case-mix factor to a broader number of health related risk adjusters not traditionally available to researchers, including the presence of co-morbidities, smoking status and American Society of Anesthesiogists score (ASA-score) and socio economic variables such as income, employment status and living alone. First we describe the data available to evaluate vascular departments in Denmark. Next we outline our methodological approach and our conceptual model drawing on the health care literature as well as describing how we judge between competing forms of risk adjustment models. In section five, we first compare mean costs and patient characteristics among departments. We then consider the influence of patient characteristics that explain costs, and then explore what cost differences persist among departments after the influence of these characteristics has been taken into account. Finally, we consider how the characteristics of patients vary among departments.

3. Data and Methods

3.1 Data

Data on costs and patient characteristics were available for 3,953 patients treated in six (out of eight) vascular departments in Denmark in 2004, which we label A-F. The cost data were taken from the National Cost database and cover the resources used during admission for intensive care, laboratory tests, procedures, ward stays etc. The National Cost Database is based on patient-level data reported by each hospital according to accounting guidelines set out by the National Board of Health and, for ancillary services, by applying a national set of relative service weights. Although subject to national guidance, there may be differences among hospitals in the way they apportion fixed or overhead costs, and this may explain some of the variation across departments in the patient-level costs they report (13). The National Cost Database is the basis of the Danish case-mix system DkDRG, under which hospitals are (partly) reimbursed.

Data on age, gender and health related patient characteristics are drawn from The Danish Vascular Registry, which is a national (clinical) registry for quality measures for all vascular hospital departments in Denmark (14). The Danish Vascular Registry was established by the Danish Vascular Society and contains information on patient specific characteristics such as age, gender, smoking status, disease status (including previous diseases) and surgical information.

Socioeconomic characteristics such as income, employment status, information about whether the patient is a pensioner and living alone are drawn from Statistics Denmark, which is a national registry for detailed statistical information on Danish society.

In table 1 all patient characteristics are presented and described. The traditional or routine risk adjustment variables (age, gender and the case-mix factor) are listed as vector $\mathbf{x}_1$, while health related variables are listed as vector $\mathbf{x}_2$ and socioeconomic variables as vector $\mathbf{x}_3$.

Table 1: Description of patient characteristics used

	Description
Routine variables (x_1):	
Casemix index	DRG-weight /average DRG weight
Age	Patient age
Age^2	Patient age x patient age to allow for a non-linear age effect
Male	Dummy variable equal 1 if patient is male
Health related variables (x_2):	
Smoker/ex-smoker	Dummy variable equal 1 if patient is smoker/ex-smoker
Emergency	Dummy variable equal 1 if patient has been subject to emergency admission
Home care	Dummy variable equal 1 if patient requires home care at discharge
Cerebrovascular	Dummy variable equal 1 if patient has been treated for TIA/amaurosis or stroke
Hypertension	Dummy variable equal 1 if patient has hypertension
Cardial	Dummy variable equal 1 if patient has been treated for cardiac disease
Pulmonal	Dummy variable equal 1 if patient has been treated for pulmonary disease
Diabetes	Dummy variable equal 1 if patient has diabetes
ASA score	Categoric variable (1-5) of the severity of the patient's condition. 1 is normal health condition and 5 is expected death within 24 hours without treatment
Intensive care > 3 days	Dummy variable equal 1 if patient has been in intensive care for more than 3 days
Socioeconomic variables (x_3)	
Net income (N=3921), DKK	The patient's net income
Unemployed (N=3936), %	Dummy variable equal 1 if patient is unemployed or on some kind of transfer income
On age pension or early retirement pension , %(N=3936)	Dummy variable equal 1 if patient is retired or on age pension
Living alone,% (N=3936)	Dummy variable equal 1 if patient is living alone

3.2 Methods

We outline our conceptual model for patients treated for vascular conditions drawing on the literature and on characteristics judged clinically relevant for vascular patients by clinicians, who collect these data as a means to evaluate quality (14).

In general we would expect that characteristics that predict costs at an individual level to have similar explanatory power at population level such as when comparing costs among hospital departments. Age and gender are the most obvious risk adjusters applied in the literature probably because they are easily and accurately observed although they are not strong predictors of individual costs. Even so, there is evidence that older age is associated with higher costs (3;5;15). As regards the characteristics included in vector $\mathbf{x}_1$ we expect age and the case-mix index to be positively related to costs but have no prior expectation with respect to gender. Patients suffering co morbidities (e.g. diabetes, pulmonal diseases) or smokers run a higher risk of suffering complications and hence experiencing a longer length of stay in hospitals (7;16-19). Also, patients who undergo anaesthesia are found to be more costly and several studies have found that a higher ASA-score is associated with a longer length of stay in hospitals (5;15). Thus patients with these additional characteristics can be expected to incur higher costs. Therefore we subsequently include the health related characteristics in $\mathbf{x}_2$ (e.g. diabetes, pulmonal diseases, smoker, ASA-score etc.) and expect them to be positive predictors of costs. We also hypothesise that adding these health related variables improves both explanatory power and provides more precise estimates of departmental performance. Finally, we include socioeconomic characteristics as there is evidence that poorer socio-economic conditions faced by patients are associated with higher costs (9;10). We hypothesise that inclusion of socio economic variables, however, has limited impact on the explanatory power of the model. This is partly because we expect that there is some correlation between health related and socio-economic variables, and partly because there is limited variation in the socio-economic characteristics across these patients. Whether the patient is living alone may, however, be a significant explanatory factor since we observe some variation across departments, and length of stay is likely to be influenced by whether the patient has access to informal care giving.

We specify a fixed effect panel data model in which all the patients across all six departments are pooled together. This panel data model has two error terms; the first term is a departmental specific unobservable effect containing unobserved characteristics of the department in which the patient was treated, and the second term is the conventional random error term, capturing unobserved characteristics of individual patients (20;21). The department specific error term is interpreted as capturing the departmental effect on costs over and above the influence of observed and unobserved patient characteristics. In the following we use the term “departmental effect” when referring to the departmental specific error term.

We estimate four models that control for progressively more patient characteristics. First we include age and gender as risk adjusters. The model is specified as:

$$c_{ij} = \alpha + \beta_1 age + \beta_2 age^2 + \beta_3 male + u_j + v_{ij} \qquad (1)$$

where c_{ij} is the cost of patient i in department j. The beta coefficients tell us how costs are influenced by age and gender respectively. We have included age^2 in order to allow for non-linear age effect. Any remaining systematic differences in costs among departments over and above the influence of the explanatory variables will be captured by the departmental effect u_j. The final error term v_{ij} captures the unexplained (random) variation in patient costs, which is assumed to be classically distributed with a zero mean and constant variance.

Second, we extend the model to include the case-mix adjustment:

$$c_{ij} = \alpha + \beta_1 \mathbf{x_1} + u_j + v_{ij} \tag{2}$$

where $\mathbf{x_1}$ is a vector that includes age, age^2, gender and the case-mix index.

Third, we include variables as vector $\mathbf{x}_2$ (health related risk adjusters):

$$c_{ij} = \alpha + \beta_1 \mathbf{x_1} + \beta_2 \mathbf{x_2} + u_j + v_{ij} \tag{3}$$

Fourth, we include socioeconomic variables as vector $\mathbf{x_3}$:

$$c_{ij} = \alpha + \beta_1 \mathbf{x_1} + \beta_2 \mathbf{x_2} + \beta_3 \mathbf{x_3} + u_j + v_{ij} \tag{4}$$

When judging the explanatory power of our models we apply the conventional measure, R^2, which measures the proportion of the variance in costs that can be explained by a set of explanatory variables (2). Examples of other measures applied in the literature are the mean absolute prediction error that is the value of the difference between actual and predicted costs or the mean prediction error, which assesses how well on average the model predicts mean costs for a defined population (22). But in addition to these standard measures, we explore what impact inclusion of progressively more patient characteristics has on the departmental effects. We do this by first assessing differences in departmental effects using an F-test. Because we perform multiple comparisons we use a 0.01 level of significance instead of 0.05, which is conventionally used for two-way comparisons only. If the null hypothesis is rejected there is no difference in departmental performance between any two departments being compared. These F-tests are performed for each model variation, in order to test whether inclusion of additional patient characteristics will change the number of departments that are statistically significantly different from each other. The number of differences in departmental effects when adding more information may go in either direction, i.e. we can either find fewer or more differences between departments. If the number of differences in departmental effects changes, it implies that that there are differences in the patient characteristics as measured by variables in $\mathbf{x_2}$ (and/ or $\mathbf{x_3}$), and that this was previously captured by the departmental effect. If the number of differences in departmental effects increases when adding more patient characteristics it suggests some of the departments managed to have the same costs even though they treat more complicated patients, level of effort they exert. Second, we explore whether the ranking of the departments is changed when adding more patient characteristics. Even though departmental effects may changes this may not lead to any material change in the relatively ranking of the departments. Therefore, we also explore whether the ranking of the departments is altered when adding more patient characteristics. We rank the departments according to the coefficients on the departmental effects, assuming a lower departmental effect reflects better departmental performance.

Finally, we estimate separate models for each specific department in order to explore what impact a particular profiles of each department has on its costs. We would always expect a greater explanatory power in the models for each department. The reason is that the departmental model most likely will provide a better fit because both the characteristics and the costs of the patients are likely to be more homogenous within than across departments. The departmental models that take account of $\mathbf{x_1}$ are written as:

$$c_i = \alpha + \beta_1 \mathbf{x}_{1\mathbf{i}} + v_i \qquad \forall j,\ j = 1,......6 \qquad (5)$$

i are the number of patients in department j (department 1-6).

And the departmental models that include both $\mathbf{x_1}$ and $\mathbf{x_2}$ are written as:

$$c_i = \alpha + \beta_1 \mathbf{x}_{1\mathbf{i}} + \beta_2 \mathbf{x}_{2\mathbf{i}} + v_i \qquad (6)$$

The departmental models that include $\mathbf{x_1}$, $\mathbf{x_2}$ and $\mathbf{x_3}$ are written as:

$$c_i = \alpha + \beta_1 \mathbf{x}_{1\mathbf{i}} + \beta_2 \mathbf{x}_{2\mathbf{i}} + \beta_3 \mathbf{x}_{3\mathbf{i}} + v_i \qquad (7)$$

4. Results

4.1 Descriptive analysis

As presented in table 2 there appear to be clear differences across departments in both costs and patient characteristics. The average cost per patient varies from 44,648 DKK at department E to 69,525 DKK at department C with an average across all departments of 59.959 DKK. Even casual observation of the patient characteristics shows differences among departments in the type of patients they treat. The case-mix index varies between departments, being lowest at department B and highest at department F implying that the latter department treats more complex patients. Cardiovascular patients tend to be elderly and the average age varies from 63.8 years at department B to 67.9 years at department E. Also, the proportion of men varies substantially with 54% at department D and 66% at department C. Most of the patients are smokers/ex-smokers, with the proportion varying among departments (from 69% to 83%). The presence of co morbidities such as hypertension also differs between departments. The percentage of patients living alone varies from 34% at department A to 50% at department B suggesting that the latter department may find it more difficult to arrange timely discharge.

The descriptive data hence beg the question as to whether the apparent differences in costs among departments can be explained by systematic differences in the characteristics of the patients treated. For instance, to what extent is the lower average cost at department E explained by a higher proportion of less complicated patients, and likewise can the higher costs per patient at department C be explained by more complicated patients? The extent of influence that patient characteristics may have on department costs is not readily discernible from the data summarised in table 2. Multivariate analysis is necessary to assess their separate and joint importance.

Table 2: Descriptive statistics on patient characteristics and costs, by departments

	A	B	C	D	E	F	Total
N	425	988	561	776	461	742	3,953
Costs (DKK)	63,070	66,783	69,525	59,634	44,648	56,095	59,959
Routine variables (x_1):							
Casemix index	0.99	0.85	1.07	1.05	0.89	1.16	1
Age	65.9	63.8	66.0	66.2	67.9	67.4	66.2
Male	0.56	0.58	0.66	0.54	0.55	0.59	0.58
Health related variables (x_2):							
Smoker/ex-smoker	0.83	0.69	0.75	0.72	0.71	0.69	0.73
Emergency	0.26	0.43	0.32	0.36	0.26	0.36	0.33
Home care	0.17	0.21	0.20	0.13	0.16	0.27	0.19
Cerebrovascular	0.15	0.09	0.09	0.20	0.19	0.18	0.15
Hypertension	0.49	0.41	0.46	0.44	0.49	0.57	0.48
Cardial	0.24	0.29	0.28	0.33	0.31	0.34	0.30
Pulmonal	0.09	0.12	0.12	0.16	0.13	0.14	0.13
Diabetes	0.17	0.16	0.13	0.18	0.15	0.17	0.16
ASA score	2.00	2.27	1.82	1.97	2.09	2.24	2.07
Intensive care > 3 days	0.03	0.03	0.09	0.09	0.02	0.10	0.06
Socioeconomic variables (x_3)							
Net income (N=3921), DKK	132,566	138,600	140,112	156,951	124,705	123,708	137,334
Unemployed (N=3936)	0.14	0.18	0.17	0.14	0.13	0.18	0.16
On age pension or early retirement pension (N=3936)	0.61	0.55	0.61	0.63	0.67	0.66	0.62
Living alone (N=3936)	0.34	0.50	0.40	0.42	0.39	0.40	0.42

4.2 Explaining variation in costs for individual patients

Results for the four risk-adjustment models are presented in table 3. As expected, we find that the explanatory power (adjusted R^2) changes when adding successively more patient characteristics (see table

3). Model 2, where the case-mix variable is included, increases the explanatory power most dramatically. When also adjusting for the health related variables ($\mathbf{x_1}+\mathbf{x_2}$) the model achieves a marginally higher explanatory power, R^2=30.0% (model 3). Adjusting for socioeconomic variables ($\mathbf{x_3}$) add even less explanatory power to the model than health related variables ($\mathbf{x_2}$). However, even though vectors $\mathbf{x_2}$ and $\mathbf{x_3}$ do not present a huge improvement in terms of R^2, the joint F-tests of these combinations of variables are significant indicating that the variables are jointly significant and should be included in the model.

We find that age, gender and the case-mix adjustment are statistically significant predictors of costs in all the models (see table 3). Age and gender provide an explanatory power similar to that in the literature (4). Older age increases the costs 1% (in model 3 and 4) for every added year. Males are around 6-7% (in model 2-4) more costly than females though in the least specified model (model 1) males are estimated to be 18% more costly than females. This change suggests that when other patient characteristics (case-mix and health related characteristics in $\mathbf{x_2}$ as well as socioeconomic characteristics in $\mathbf{x_3}$) are added the impact of age and gender is significantly reduced. This is because some of the variance attributed to age and/or gender in model 1 is being captured (more correctly) by the health related and socioeconomic variables. Hence, the best estimate of the age effect and the effect of other variables is from model 4, the most fully specified model.

The coefficient for the case-mix variable is highly statistically significant and captures much of the variation in patient level costs. For the health related characteristics we find that treatment costs are higher for smokers, emergency patients and those with a higher ASA-score (model 3). Smokers are between 15 and 17% more costly than non-smokers, and emergency patients are 12-13% more costly to treat than other patients. Patients receiving home care after hospitalisation are 9% cheaper to care for suggesting there may be some substitution of care input between the hospital department and other care providers. Also, use of intensive care for at least 3 days reduces costs by 12% in model 3, which probably can be explained because such patients are more likely to die during their admission.

The coefficients for patients on pensions (age pension or early retirement pension) and patients living alone are positive and statistically significant suggesting that these patients incur higher treatment costs. Pensioners are 9% more costly and patients living alone are 5% more costly. The other socioeconomic variables are not statistically significant.

Table 3: Estimating costs using different patient characteristics (* if significant at 5%)

	Model 1	***Model 2***	***Model 3***	***Model 4***
	Age and gender and dep. effects	$\mathbf{x_1}$ and dep. effects	$\mathbf{x_1} + \mathbf{x_2}$ and departmental. effects	$\mathbf{x_1} + \mathbf{x_2} + \mathbf{x_3}$ and dep. effects
Constant	8.95*	9.15*	9.21*	9.37*
Routine variables (x_1):				
Age	0.03*	0.02*	0.01*	0.01*
Age2	-0.00*	-0.00*	-0.00	-0.00
Male	0.17*	0.07*	0.06*	0.07*
Case-mix	-	0.42*	0.43*	0.43*
Health Variables (x_2) :				
Smoker/ex-smoker	-	-	0.15*	0.14*
Emergency	-	-	0.12*	0.13*
Home care	-	-	-0.09*	-0.09*
Cerebrovascular	-	-	0.04	0.05
Hypertension	-	-	0.03	0.02
Cardial	-	-	-0.02	-0.02
Pulmonal	-	-	0.09*	0.10*
Diabetes	-	-	0.02	0.02
ASA score	-	-	0.03	0.03
Intensive care > 3 days	-	-	-0.12*	-0.11
Socioeconomic Variabels (x_3)	-	-	-	
Net monthly income (1.000)	-	-	-	0.00
Transfer income and/or unemployed	-	-	-	0.02
Pensioner/early retirement pension	-	-	-	0.09*
Living alone	-	-	-	0.05*
Departmental effects:				
A	0.2348	0.2419	0.2251	0.2294
B	0.1384	0.1885	0.1818	0.1762
C	0.1392	0.1180	0.1279	0.1289
D	-0.0748	-0.1008	-0.1132	-0.1144
E	-0.2277	-0.1728	-0.1432	-0.1383
F	-0.2043	-0.2661	-0.2483	-0.2425
R^2	8.3%	29.1%	30.0%	30.1%**

**Note: The explanatory power for model 4 is not directly comparable with model 1-3 as merging the socio-economic data with the rest of the data meant that we lost approximately 50 patients that we could not find in the register. We however estimated models 1-3 with the same data as for model 4 and found that it did not change for model 1 and 2 but declined a little for model 3 – to 29.9% which is then comparable to model 4.

4.3 Interpreting departmental effects

The results reported in the previous section focus on explaining variation in patient costs for the sample as a whole. The departmental effects u_j can be interpreted as indicative of departmental performance in controlling costs, after taking into account the types of patients each department treats. In this section we ask two questions. First, are there significant differences between departments in their performance? Second, does the significance of these differences depend on which patient characteristics we control for?

As exhibited in table 3 we find that the departmental effects vary between departments and across various model specifications suggesting that relative departmental performance might change when adding more patient characteristics. Department E and F do, however, have the best departmental performance across all models (lowest departmental effects).

When assessing the significance of estimated differences in departmental effects we apply an F-test. In table 4 differences in departmental effects between two departments being compared are presented. An asterix means that there is a significant difference ($p<0.01$) in departmental effect between the two departments that are the subject of comparison. As the upper diagonal of table 4 illustrates, when adjusting for only age, gender and case-mix we find significant differences in the departmental effects in 11 comparisons, mainly for departments C, D and F compared to other departments (and each other). When also adjusting for the health related variables ($\mathbf{x_1} + \mathbf{x_2}$) we find significant differences for 10 comparisons which implies only a marginal difference between departmental effects derived from model 2 ($\mathbf{x_1}$) and model 3 ($\mathbf{x_1} + \mathbf{x_2}$). The key result is that the difference between departments A and C found when controlling for only age, gender and case-mix is no longer significant. This suggests that the cost difference between these departments is not due to efficiency but to other health related characteristics of their patients. Adding socioeconomic characteristics does not change the results (not shown).

Nor do the different model specifications have a substantial effect on the ranking of the departments. Taking account of additional health characteristics in $\mathbf{x_2}$ and/or socioeconomic characteristics in $\mathbf{x_3}$ does not change the ranking of the departments. In table 5 the departments are ranked from 1 (best) to 6 according to the departmental effects in the four risk adjustment models, and we find that the only factor changing the ranking (slightly) is the case-mix factor.

The results suggest that including only the traditional variables such as age, gender and case-mix adjustment leaves some unexplained heterogeneity in costs, which is captured in the departmental effect and interpreted as a difference in the departmental performance. However, inclusion of health related variables in $\mathbf{x_2}$ only slightly improves the model with regard to drawing inferences about departmental effects. The results imply that the most important characteristics to take into account when comparing performance across departments are the age, gender and case-mix of patients.

Table 4: Costs, differences in departmental effects (* if significant at 1%)

$x_{1+}x_2$ \ x_1	A	B	C	D	E	F
A			*	*	*	*
B				*	*	*
C				*	*	*
D	*	*	*			*
E	*	*	*			
F	*	*	*	*		

Table 5: Ranking of the departments according to departmental effects

Department	Age, age^2 and gender	Age, age^2, gender and case-mix ($\mathbf{x_1}$)	$\mathbf{x_1} + \mathbf{x_2}$	$\mathbf{x_1} + \mathbf{x_2} + \mathbf{x_3}$
E	1	2	2	2
F	2	1	1	1
D	3	3	3	3
B	4	5	5	5
C	5	4	4	4
A	6	6	6	6

4.4 Underlying reasons for differences in departmental performance

Causal observation of the descriptive data presented in Table 2 suggests that there are systematic differences across departments in the types of patients each treats. In the previous section we found significant differences in departmental effects after controlling for various patient characteristics. These results are based on data pooled across departments, and thus these estimates provide an indication of the average influence of each explanatory variable across the full sample of patients. It may be, however, that the influence of these variables varies from one department to the next and as such costs may reflect differences among departments in how they treat their patients or (perhaps more likely) in the characteristics of their patients i.e. differences in the profiles of the patients across departments. If the profiles of the patients vary across departments this may then influence costs differently. In this section we explore whether the estimated differences in departmental effects are (partly) caused by differences in patient characteristics.

As exhibited in table 6 there is some variation in R^2 between the individual departments, when only traditional risk adjustment variables ($\mathbf{x}_1$) are included. R^2 varies from 18.4% (department E) to 33.6% (department F), suggesting that these variables are more important for patient level costs in some departments than in others. Especially the models for department D and F have a high explanatory power indicating that more of the variation in costs is related to the traditional risk adjusters compared to the other departments. The strengths of the relationship between costs, age, gender and the case-mix factor respectively vary across departments. This suggests that there are differences in the profiles of the patients across departments and it may also reflect differences in how the various departments treat patients according to their profile. We do not know whether differences in the coefficients of the various variables reflect either differences in the profiles of the patients treated or whether departments treat patients with various profiles differently.

Table 6: Cost estimations with traditional risk adjusters ($\mathbf{x_1}$), individual department models, (* if significant at 5%)

	A	B	C	D	E	F
Constant	8.80*	9.48*	10.03*	9.64*	7.66*	8.57*
Age	0.04*	0.02*	0.002	-0.001	0.07*	0.03*
Age^2	-0.00	-0.00*	0.00	0.00	-0.00*	-0.00
Male	0.02*	0.07*	0.08	0.13*	-0.02	0.07
Case-mix	0.44*	0.58*	0.39*	0.50*	0.54*	0.34*
R^2	23.9%	24.5%	25.2%	30.5%	18.4%	33.6%

Extending the model to include $\mathbf{x_1} + \mathbf{x_2}$ (table 6), R^2 ranges from 19.8 to 35.1%, and improves more for some departments than others (see table 7). The strengths of the relationship between the additional patient characteristics in $\mathbf{x_2}$ such as smoking, emergency, diabetes and costs vary across departments. This suggests that differences in departmental performance may partly be explained by differences in the profiles of the patients treated in each department or partly by how departments treat patients with different profiles.

Table 7: Cost estimations with age, gender, case-mix and additional health related characteristics ($\mathbf{x_1} + \mathbf{x_2}$), departmental models, (* if significant at 5%)

Department	**A**	**B**	**C**	**D**	**E**	**F**
Constant	8.87*	9.42*	9.89*	9.47	7.46*	8.84*
Routine variables:						
Age	0.03	0.02*	-0.008	-0.00	0.07*	0.02
Age^2	-0.00	-0.00*	0.00	0.00	-0.00*	-0.00
Male	0.03	0.10*	0.06	0.07	0.01	0.03
Case-mix	0.38*	0.60*	0.40*	0.57*	0.49*	0.35*
Health related variables:						
Smoker/ex-smoker	0.15*	0.03	0.14	0.18*	0.12	0.21*
Emergency	0.17*	-0.05	0.11	0.29*	0.18*	0.00
Home care	0.04	-0.07	-0.16	0.05	-0.08	-0.18*
Cerebrovascular	0.05	-0.11	0.14	0.18	0.06	0.07
Hypertension	0.06	-0.04	0.06	0.06	-0.06	0.06
Cardial	0.05	0.07	-0.20*	-0.03	-0.08	0.03
Pulmonal	-0.07	0.20*	-0.03	0.15	0.18*	-0.02
Diabetes	0.01	-0.08*	0.01	0.08	0.07	0.06
ASA score	0.15*	0.03	0.20*	-0.05	0.06	-0.07
Intensive care > 3 days	-0.25	0.11	0.19	-0.50*	-0.35	0.03
R^2	29.6%	25.2	27.6%	34.1%	19.8%	35.1%

Adding socio-economic variables hardly has any effect on the explanatory power, see table 8.

Table 8: Cost estimations with all explanatory variables ($\mathbf{x_1} + \mathbf{x_2} + \mathbf{x_3}$), departmental models, (* if significant at 5%)

Department	A	B	C	D	E	F
Constant	9.37*	9.38*	9.81*	9.55*	7.89*	8.77*
Routine variables:						
Age	0.03	0.02*	-0.01	-0.01	0.06*	0.02
Age^2	-0.00	-0.00*	0.00	0.00	-0.00*	-0.00
Male	0.04	0.10	0.05	0.09	0.01	0.04
Case-mix	0.36*	0.60*	0.41*	0.56*	0.49*	0.36*
Health related variables:						
Smoker/ex-smoker	0.13	0.03	0.16*	0.19*	0.12	0.20*
Emergency	0.17*	-0.03	0.12	0.29*	0.18*	0.01
Home care	0.02	-0.07	-0.17	0.04	-0.08	-0.20*
Cerebrovascular	0.03	-0.10	0.14	0.18*	0.00	0.05
Hypertension	0.06	-0.04	0.06	0.05	-0.08	0.05
Cardial	0.05	0.08	-0.20*	-0.04	-0.08	0.03
Pulmonal	-0.07	0.23*	-0.02	0.16	0.17	-0.02
Diabetes	0.01	-0.08	0.01	0.08	0.06	0.05
ASA score	0.15*	0.03	0.20*	-0.06	0.06	-0.09*
Intensive care > 3 days	-0.24	0.10	0.18	-0.45*	-0.31	0.01
Socioeconomic variables:						
Net monthly income (1.000)	-0.00	0.01	0.01	0.00	-0.00	0.00
Transfer income and/or unemployed	0.07	-0.00	-0.11	0.10	0.13	0.18
Pensioner/early retirement pension	-0.01	0.15	-0.04	0.02	0.18	0.23*
Living alone	0.08	0.04	0.05	0.04	-0.00	0.08
R^2	30.8%	25.4%	27.83	33.9%	19.9%	35.2%

When running a model which includes variables $\mathbf{x_1}$ and $\mathbf{x_3}$ in addition to age and gender in order to verify whether variables in $\mathbf{x_2}$ and variables in x_3 serve as substitutes (not shown), we find that the explanatory power of this model is approximately equivalent to that of the model which includes age, gender, $\mathbf{x_1}$ and $\mathbf{x_2}$. This suggests that there is some degree of substitution between additional health related characteristics ($\mathbf{x_2}$) and socio-economic characteristics ($\mathbf{x_3}$).

5. Discussion

In this paper we have explored whether taking account of health related risk adjustment variables such as smoking status, ASA-score, diabetes etc. as well as socioeconomic variables such as income, employment and living alone provides us with a model with higher explanatory power that is better able to identify departments that perform better or worse than other departments. Moreover, we have explored reasons for differences in departmental effects after taking account of the patient characteristics of the patients they treat.

We found that the case-mix factor is the most important explanatory variable, a result which accords with results from the literature (4;15). Also, the case-mix factor changes the ranking of the departments. Extending the model to also include health related risk adjustment factors increases the explanatory power only marginally. However, some of the health related variables such as smoking, emergency, home care and ASA-score are individually significant suggesting it is important to take account of these characteristics when explaining patient costs across different hospital departments. In contrast other characteristics such as presence of diabetes and hypertension appear to be of lesser importance in explaining costs for vascular patients. Socioeconomic patient characteristics such as whether the patient is on a pension or lives alone have a positive and statistically significant impact on costs, suggesting that patients who are retired and patients living alone are more costly to care for.

Based on the inferences drawn in relation to the relative performance of departments, we have found that inclusion of the health related variables only slightly change the comparisons across departments. The inclusion of socio-economic variables yields no such effect and provides little addition to the explanatory power of the model, but this may be due to the fact that most cardiovascular patients are in similar socio-economic situation hence there being limited variation in these characteristics.

There are some issues around coding of diagnosis according to DRG, which we have not been able to resolve. Looking at the two departments with the highest and the lowest case-mix index begs the question as to whether this is a true reflection of case-mix or might be (partly) due to differences in coding practice across departments. The case-mix index is relatively low at department B even though this is a specialised hospital. There may also be differences among departments in how they organise care and this may have a bearing on costs. At department B some groups of patients appear to be admitted for inpatient treatment who would be outpatients at other departments. We ran individual departmental models which excluded the case-mix factor, but included age, gender and health related characteristics (i.e. diabetes, emergency, ASA-score etc.) as explanatory variables. The explanatory power was significantly reduced. Our results suggest that omission of case-mix adjustment has a varied impact on the explanatory power of department specific models. It seems that the case-mix adjustment captures more of the variation in costs for department D and F, and likewise that the health characteristics captures more of the variation in costs for especially department A but also for department B. That said, substituting the case-mix variable with health related characteristics did not cause any changes in departmental effects but slightly changed the ranking of the departments as department B now ranks one higher and department C one lower.

6. Conclusion

It can be concluded that adding health related or socio-economic patient characteristics only slightly improves our model in terms of explanatory power or when drawing inferences about the relative performance of vascular departments suggesting the extra costs of collecting these additional data are not worth incurring. An important finding in our study is the case-mix factor, which adds considerable explanatory power as compared to including age and gender only. Moreover, adding the case-mix factor also slightly changes the ranking of the departments.

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