# How much should be paid for specialised treatment?

Silvio Daidone
University of York

Andrew Street
University of York

Centre for Health Economics, University of York, Heslington, YORK, YO10 5DD, UK. silvio.daidone@york.ac.uk, phone: +44 (01904)321421, andrew.street@york.ac.uk, phone: +44 (01904)321445

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## Abstract

If specialisation is supposed to reduce costs why is reimbursement often more generous for specialist than non-specialist hospitals? Specialist hospitals claim that gains from specialism are offset because they attract patients with more complex care requirements. We assess the foundation for this claim. For 2008/9 we match Hospital Episode Statistics to Reference Cost data and to the Specialised Services National Definition Sets which identifies specialised care during patients' hospital stay. Our sample consists of 12million patients in 163 hospitals. We estimate multiple regression models to explain why costs vary among patients, focussing on markers of specialised care as explanatory factors. We test the robustness of results to choices about how costs are calculated, how the regression models are specified and how receipt of specialised care is determined. We find that costs are higher than for other patients allocated to the same Healthcare Resource Group (HRG) if a patient has one of the following types of specialised service: cancer (13-18%), spinal (28-31%), neurosciences (23-24%), cystic fibrosis (26-38%), children's (15-20%), rheumatology (13-25%), colorectal (18-21%) and orthopaedic (20-21%). No other types of specialised care are shown to lead to significantly higher costs. The implication for payment policy is that patients with these markers might be paid an additional top-up over and above the tariff associated with the HRG to which they are allocated.

**Keywords:** Hospital specialization, prospective reimbursement, top-ups, costs.

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## 1. Introduction

In April 2002 the Department of Health in England introduced a new system of hospitals' reimbursement, called "Payment by results" (PbR). Similarly to other healthcare systems, PbR uses a fixed prospective payment that links a hospital's income to the number and case mix of patients treated. Under PbR, payments for hospital care are defined in terms of the healthcare resource group (HRG – the English version of diagnosis related groups) to which each patient is allocated.

Some specialist hospitals in England are paid "top-up" payments over and above their PbR income. England is not alone in this: specialist hospitals in other countries with prospective payment also receive additional income over and above that which they would receive from prospective payments alone (Mechanic et al., 1998, Langenbrunner and Wiley, 2002). Such practice seems to go against received economic wisdom dating back at least to Adam Smith's reflection on specialisation and comparative advantage. If specialisation is supposed to reduce costs why is reimbursement often more generous for specialist than non-specialist hospitals?

One possibility is, simply, that specialist hospitals are able to exercise greater bargaining power than non-specialist hospitals in negotiating with their funders, a possibility that we shall return to in due course.

Another possibility is that there is a basis for the higher payments: specialist hospitals might claim that cost-reducing gains from specialism are offset because they attract patients with more complex care requirements. HRGs, after all, are imperfect measures of casemix: any categorisation will inevitably combine patients with below and above average costs. This may be problematic if there is a reason that has not been accounted for why patients within the same HRG have different costs. One reason is that some patients in the same HRG require more expensive specialised care while others do not. This paper explores that possibility.

The main goal is to assess the extent to which costs differ for patients that receive specialist services from those that do not receive them, taking account of other factors that might explain costs. These factors include the HRG to which the patient is assigned, various socio-demographic, diagnostic and treatment-related characteristics of the patient, and the hospital in which the patient is treated.

In what follows we first discuss what might be meant by specialised care. We then describe the economic model, by addressing some issues in the estimation of cost functions for hospital services. In section four we discuss some econometric issues and show our estimation equations, which investigate whether variations in cost are explained by whether or not a patient received a specialised service. Then in section five we provide a presentation of the data and some descriptive statistics, followed by results in section six. We draw conclusions in section seven.

## 2. What constitutes specialised care?

Dranove argues that, under prospective payment, potential cost savings from specialization derive from two sources (Dranove, 1987). First, hospitals may be relatively efficient and use their production cost advantage profitably to produce particular types of treatment. Specialisation, therefore, consists of undertaking a narrow

array of services. Zwanziger et al. argue that this strategy should curb costs, for instance, by eliminating or reducing low-volume services (Zwanziger et al., 1996).

The second cost-saving strategy motivation stems from differences in the cost of treating patients within HRGs, with hospitals seeking to attract less costly patients (a practice termed "cream-skimming"). If this practice occurs, aggregate hospital expenditures need not fall and the effectiveness of the system decreases. Farley and Hogan provide a definition of specialization, which relates to deviations of case-mix proportions from what might be considered "normal"(Farley and Hogan, 1990). A hospital compares the services it provides against some reference group and its cost behaviour basically depends on the relative difference in case-mix variation. They found a systematic negative relationship between cost and their index of specialization and argue that the reasons for average costs to decline as case-mix specialization increases include inter-hospital differences in productive efficiency, product-specific economies of scale, and diseconomies of scope. Eastaugh also derived similar results in a sample of US short-term nongovernmental hospitals for the period 1999-2008 (Eastaugh, 2009).

The possibility of cream skimming is tempered in public health systems where hospitals are prohibited from selecting less risky patients. But selection might work in the opposite direction – patients might chose to go to specific hospitals and these patients might have systematically higher costs than others. If such behaviour occurs, the selected hospitals will have more costly patients than average. The classification system used to distinguish between diverse treatments is unlikely to account for all cost variation among patients, opening up the possibility that hospitals claim for additional payments because their patients are somehow "different". By comparing costs across hospitals, the regulator can guard against this risk (Holmström, 1979, Laffont and Tirole, 1993).

## 3. Estimating hospital cost functions

In this work we posit a representation of the hospital which differs from neoclassical or behavioural models that assume a relationship between costs and large categories of inputs and some output measures. These approaches may suffer serious problems with aggregation bias or model specification, as has been also shown in an influential paper by Newhouse (Newhouse, 1994).

Instead our representation is closer to that of Harris who recognised that hospital care is tailored to the specific characteristics and requirements of each individual patient (Harris, 1977). The rationale is that the patient from the moment of admission to discharge incurs in a treatment course customized to his specific medical needs. The implication of this is that the production functions of inpatient services are best defined using the patient as unit of analysis. Bradford et al. used this approach to compare the costs for two competing technologies for the treatment of coronary artery disease, utilizing data from a large Southern hospital (Bradford et al., 2001). Laudicella et al. and Kristensen et al. adopted a similar approach in their respective analyses of the costs of obstetrics specialties and diabetes care in English hospitals (Laudicella et al., 2010, Kristensen et al., 2010). The main difference with respect to these authors is that they focused their analysis on specific types of treatment, while the analysis here considers the whole population of inpatient admissions in England.

For the description of the model we follow largely the formalization of Bradford et al. Here we summarize the main aspects. Patients are admitted into the hospital and face a production function which depends on both resources used and patient-specific characteristics

$$\boldsymbol{h}_{ih} = F_i(\boldsymbol{x}_{ij}, \theta_i) \qquad i=1...I \quad j=1...J \tag{1}$$

where $\mathbf{h}_{ih}$ is a vector of the $j$ bundles of services (ie HRGs) supplied to the i$^{th}$ patient, $\boldsymbol{x}_{ih}$ is a vector of inputs supplied to the i$^{th}$ patient to produce the $h^{th}$ output and $\theta_i$ are patient-specific characteristics. Patients derive a utility $U$, which is a function of the service bundle utilised by the patients

$$U_i = U(\underline{\boldsymbol{h}}_i) \tag{2}$$

The hospital trades-off the utility of some patients against that of others and the criterion to carry off this task is given by a social welfare function $W(U) = W(U_1,..., U_I)$, which aggregates individuals' utilities into social utilities. Social welfare functions may have lots of interesting properties, such as *nonpaternalism*, *paretian*, *symmetry* and *concavity*.[1] In this setting, $W(U)$ is purely utilitarian and has the form $W(U)=\Sigma_i U_i$, where increases or decreases in patients' utilities translate into identical changes in social utility.

At the same time we assume that hospitals do not operate under financial losses. We indicate hospital revenue with $\boldsymbol{R}$, which is a function of the service bundles supplied to patients and, consequently, depends on resources used, and $\underline{\boldsymbol{P}}$ is a vector of input prices. The hospital's problem is therefore

$$\max_{\boldsymbol{x}} \boldsymbol{W} = \sum_{i=1}^{I} U(\underline{\boldsymbol{h}}_i) \tag{3}$$

$$\text{s.t. } \boldsymbol{R}(\underline{\boldsymbol{x}}_1, \dots, \underline{\boldsymbol{x}}_I) - \sum_{i=1}^{I} \underline{\boldsymbol{P}}\ \underline{\boldsymbol{x}}_i \geq 0$$

To maximize social welfare function bounded by the hospital budget constraint, we set up a Lagrangian and, given the convexity of the utility possibility set, the first-order conditions, unreported here, are sufficient for an interior solution. With the optimal input quantities obtained from the resolution of the maximization problem, we are able to define an implicit production function for the $j^{th}$ service bundle, which is dual to the following cost functions

$$C_{ij} = C(\underline{\boldsymbol{P}}, \theta_i) \tag{4}$$

Where $C_{ih}$ is the cost incurred by the hospital to provide the $h^{th}$ intermediate output to the $i^{th}$ patient. With this model each patient faces a set of cost functions which is specific to each bundle of services consumed. Empirical implementation of this approach requires comprehensive data on individual patients.

[1] See Mas-Colell et al. (1995) for a good review of the properties of social welfare functions.

## 4. Econometric considerations

The behavioural cost function is of the form

$$C_{ihk} = f\left(\boldsymbol{h}_{ih}, \underline{\boldsymbol{P}}_i, \boldsymbol{S}_n, \theta_i\right) + \epsilon_{ik} \quad (5)$$

where $k$ represents the hospital and $\mathbf{S}_n$ the vector of $n$ specialised services. $\epsilon_{ik} = u_k + v_{ik}$ is the overall error term which is decomposed in two parts: i) a random error term, $v_{ik}$ , for the $i^{th}$ patient within the $k^{th}$ hospital with zero mean and constant variance $\sigma_v$; ii) a random hospital effect $u_k$ which we assume again to have zero mean and constant variance $\sigma_u$. We also assume that patients and hospitals are uncorrelated, i.e. $cov(u_k, v_{ik}) = 0$. This is a reasonable assumption whenever unobserved patient case-mix characteristics are uncorrelated with hospitals.

Some modifications to the standard model have to be introduced in order to make estimation feasible. Firstly, for each patient we would need data on input prices paid by each hospital. To cope with this severe data constraint costs are adjusted by the market forces factor (MFF), which is an index of geographical variation in the prices of land, buildings, and labour (Department of Health, 2008a). Unavoidable price differences in actual costs incurred by different hospitals in producing healthcare services are reflected in the indicator.

Secondly, we face severe problems when comparing jointly the overall population of patients, who receive very diverse types of treatment. It would be unfeasible to introduce dummy variables for all 1,400 HRGs as these would critically slow down estimation and introduce incidental parameter biases. We decided therefore to drop the HRGs from the right-hand side of equation (5) and, instead, standardize each patient's cost by the mean cost of all other patients allocated to the same HRG. Thus our dependent variable is defined as the patient's cost relative to the average cost of patients in the same HRG: $\tilde{C}_{ik} = {}^{c_{ihk}}/_{\widehat{c_h}}$ where $c_{ihk}$ is the cost of patient $i$ in HRG $h$ in hospital $k$ and $\widehat{c_h}$ is the national average cost of all patients allocated to HRG $h$. We consider models in which the dependent variable is in linear and log forms.

We compare results from different model specifications. Our base OLS model simply regresses the standardised cost against the full set ($n$=1…$N$) of specialised care markers ($S$), which take the form of dummy variables. The model is specified as:

$$\tilde{C}_i = \propto + \sum_{n=1}^{N} \beta_n S_{ni} + \varepsilon_i \quad (6)$$

Where the $\beta's$ are the parameters of interest: if positive and significant, a patient with the specialist care marker has higher costs than do other patients allocated to the same HRG. In interpreting the results, note that the coefficients on specialised markers, the βs, represent the difference in standardised costs between specialised and unspecialised services. In fact, if we think about expectations, since we are assuming the zero mean conditional assumption $E(\varepsilon|S_i, \mathbf{S}, \mathbf{X}) = 0$, then $\beta_i = E(y_i|S_i=1, \mathbf{S}, \mathbf{X}) - E(y_i|S_i=0, \mathbf{S}, \mathbf{X})$. In order to get a more easily interpretable measure like the percentage increase, $g$, we need to compute the marginal mean for unspecialised services, so that

$$g_i = \frac{E(y_i|S_i = 1, \boldsymbol{S}, \boldsymbol{X}) - E(y_i|S_i = 0, \boldsymbol{S}, \boldsymbol{X})}{E(y_i|S_i = 0, \boldsymbol{S}, \boldsymbol{X})} * 100$$

$$= \frac{\beta_i}{E(y_i|S_i = 0, \boldsymbol{S}, \boldsymbol{X})} * 100 \qquad (7)$$

We consider also two intermediate specifications. In the first one, we estimate equation (6) as a random effects model[2]

$$\tilde{C}_{ik} = \propto + \sum_{n=1}^{N} \beta_n S_{nik} + u_k + v_{ik} \qquad (8)$$

Equation (8) thus recognises the multi-level structure of the dataset, with patients ($i$=1…$I$) clustered within hospitals ($k$=1…$K$). The $u_k$ is the random effect. This captures the effect of the hospital on the cost of any particular patient treated in the hospital over and above the other explanatory variables included in the model (here, whether and what type of specialised care the patient received). The random effect, then, can be interpreted as a measure of relative hospital performance in controlling costs or, in other words, of relative hospital efficiency.

Equations (6) and (8) include only the specialised care markers to explain why the costs of any individual patient might differ from the costs of other patients allocated to the same HRG. In reality, of course, an individual's costs will vary because of other characteristics than merely whether or not they received specialised care and the hospital in which they are treated. To some extent the HRG to which the patient is allocated account for these characteristics, but HRGs can only do this imperfectly. There will always be imprecision in the way that patients are categorised to a limited set of HRGs, with some patients having higher or lower costs than others categorised to the same HRG. If the characteristics that might explain an individual's cost are imperfectly accounted for in the construction of HRGs and are not included as explanatory variables in the regression model, their omission might lead to two problems:

- First, the influence of the explanatory variables that are included in the model might be biased. Here this would imply that the estimated influence on cost of whether or not a patient receives specialised care would be imprecise. The influence of specialised care would be *over*-estimated if the omitted variables are both cost-increasing and positively correlated with receipt of specialised care. This might be the case, for instance, for patients with more complex diagnoses than typical for other patients in their HRG. If these diagnostic characteristics were also included in the model, the result would be a lower estimated influence of specialised care on cost.
- Second, the estimated hospital (random) effects might be biased and, if so, would provide an imperfect measure of relative hospital efficiency. This bias would

[2] We estimated also a fixed effects specification and compared the models by Hausman tests. Since the difference in coefficients is not statistically significant, random effects is more efficient. The fact that the FE and RE models yield similar results is not surprising, given the large amount of observations per hospital.

arise if there are *systematic* differences across hospitals in the type of patients treated within each particular HRG. For instance, one hospital might attract more complex patients with more diagnostic problems. If this is not taken into account the hospital will appear to have higher costs than it should have given the (inaccurately measured) profile of the patients that it treats.

The solution to both problems is, of course, to take these characteristics into account by including them as explanatory variables in the model. We consider the extent to which patient characteristics, over and above whether they have received specialised services, explain costs. To do this, we include a set ($m$=1…$M$) of additional explanatory variables ($X$) describing each patient. We do this first for an expanded version of equation (6):

$$\tilde{C}_i = \propto + \sum_{n=1}^{N} \beta_n S_{nik} + \sum_{m=1}^{M} \gamma_m X_{mi} + \varepsilon_i \qquad (9)$$

Finally our full model allows for patient characteristics and for clustering of patients within each hospital. Estimated as a random effects model, this takes the general form:

$$\tilde{C}_{ik} = \propto + \sum_{n=1}^{N} \beta_n S_{nik} + \sum_{m=1}^{M} \gamma_m X_{mi} + u_k + v_{ik} \qquad (10)$$

Another aspect that we have to consider in this econometric framework is the distribution of health care cost data. It is widely known that health cost/expenditures data are highly skewed and in some settings also with zero mass (Manning and Mullahy, 2001, Beeuwkes Buntin and Zaslavsky, 2004, Basu and Rathouz, 2005). Usual econometric OLS methods may yield biased and/or less precise estimates of means and marginal effects, since results may not be robust to tail problems. In our case, the zero mass issue does not appear, but the skewness of inpatient hospital costs is confirmed (see Figure 1).

A sound approach would be then to compare different estimators, evaluating pros and cons. OLS on untransformed dependent variables has the great advantage of being simple, without retransformation problem and marginal effects are easy to calculate. The main drawbacks are the possible out-of-range predictions and lack of robustness in small to medium sized datasets. Indeed, the latter setback clearly does not apply in this work given the large amount of available observations (see data section for details).

Estimates with OLS for log transformed costs or their Box-Cox generalized version are often more precise and robust than direct analysis of unlogged dependent variable. However these advantages are counteracted by the retransformation problem and some version's coefficients are not directly interpretable. In this setting we are not interested in the predicted values of the dependent variable per se, but actually in the marginal effects, especially those of the dummy variables representing specialised care. The percentage increase in costs for specialised services following Kennedy (Kennedy, 1981) is

$$g_i = exp\left(\beta_i - \frac{\widehat{Var}(\hat{\beta}_i)}{2}\right) - 1 \qquad (11)$$

## 5. Data issues and descriptive statistics

We analyse the hospital episode statistics (HES) for all patients discharged from each English Acute Care Hospital Trust in 2008/2009. HES comprise individual patient records defined as a Finished Consultant Episode (FCE) about every NHS patient admitted to hospital in England. We link the episodes for each patient in order to construct provider "spells" that measure the time a patient spends in each provider (Castelli et al., 2008). Our analytical sample consists of 12,154,599 patients.[3]

Each patient record contains socio-demographic (e.g. age, gender, income deprivation in their area of residence) and clinical information (e.g. diagnoses, procedures performed). We look at the information in each HES record to ascertain whether or not specialised care was received. A patient is assigned a specialised care marker if: a) one of the ICD10 codes designated in the Specialised Services National Definition Set (SSNDS) is present in their HES record (an individual might have more than one marker) (NHS Specialised Services, 2010); b) they were treated at an eligible provider, because non-eligible providers should not be providing specialised services.[4] Specialised activity may not necessarily be more costly or complex, since the SSNDS defines activity as specialised if it requires a planning population of over 1 million people, without any specific relation to resource use. This classification differs from more classical definitions of what can be deemed specialised or not.

In 2008/2009, for approximately 1.5m spells it was indicated that some kind of specialised activity was delivered as part of the treatment package. Table 1 reports the number of patients with particular conditions who receive specialised services, showing, for instance, that 360,000 patients having renal care received specialised services. For the vast majority of patients, just one specialised service was delivered but around 50,000 patients received more than one specialised service.

Each patient record in HES is mapped to cost information supplied by every English hospital. All hospitals are required to apply a standard top-down costing methodology to produce costs for each elective day case, elective inpatient, and non-elective HRG in

[3] From an initial population of 14,209,444 patients the final sample used in our analysis is reduced because 1) we considered only those patients treated in NHS acute hospitals. Hence, patients treated in mental health, ambulance and primary care trusts and private providers are excluded. 2) HES episodes with missing identifier codes are dropped, because they cannot be matched to the reference cost database. 3) We excluded duplicate observations and those showing data inconsistencies, such as admission date posterior to discharge or patients with different ethnicity codes within a spell. 4) Reference costs are not reported for some types of activity, notably renal dialysis, well babies, and mental health, so these patients are omitted. 5) Some hospitals did not provide reference cost data in a form that could be matched to HES records. This was particularly so for South London Healthcare Trust, which may be due to its recent creation as an amalgamation of three smaller hospitals; Western Sussex Hospital NHS Trust, which may also be due to its recent creation as a merger of the Royal West Sussex and Worthing & Southlands Hospitals; and Cambridge University Hospitals NHS Foundation Trust. 6) Finally we excluded those episodes with a length of stay in excess of 365 days.

[4] Results are robust to whether or not this latter condition is used to define receipt of specialised care, see Daidone & Street (2010).

each of their departments (Department of Health, 2008b). This means that total hospital costs are progressively cascaded down first to treatment services (wards, theatres, pharmacy, etc), then to specialties, and finally to HRGs. These costs are calculated on a full absorption basis, meaning that they should reflect the full cost of the service delivered. We map costs to each patient according to hospital and department in which they were treated, their admission type, the HRG to which they were allocated, and their length of stay, by applying the process described in the appendix.

Reference costs are reported for individual episodes. Around 10% of spells are multi-episode, and these patients are likely to be more costly than single-episode spells. This is important for our analysis because patients who receive specialised care are more likely to have multi-episode spells. In the absence of an agreed methodology about how to construct spell-level costs, the analysis that follows assumes that the cost of the provider spell as equivalent to the sum of the costs of each FCE in the spell.[5] Summary statistics of the costs are provided in Table 2 for all patients treated in 2008/9 and according to whether or not they received specialised care.

Irrespective of the way in which costs are calculated, there are clear differences in costs between patients who do and do not receive specialised care, which are also confirmed by simple t-tests (1% significant differences). This raises the question of what drives these differences in cost, particularly whether or not the difference is due solely to receipt of specialised care.

One reason is that patients differ in other ways. Patient characteristics are derived from information contained HES and, in some of our models, we included the following set of variables:

- The patient's age and gender (and interactions of these).
- Whether the patient ethnicity was white;
- Regional and urban location of the hospital;
- The number of episodes comprising the patient's provider spell;
- Whether the patient was admitted as an emergency;
- Whether the patient died;
- Whether a patient was transferred into the hospital or is transferred to another hospital, and whether the hospitals in question were eligible or non-eligible providers of specialist services;
- The presence of various diagnostic markers that may influence cost over and above the HRG to which the patient is allocated. These markers depend on the presence of specific ICD10 codes in the HES record and include such things as: hypertension, allergies, obesity, diabetes, history of past disease, etc;
- The socio-economic conditions of the area in which the patient is resident.

In Table 3 we provide some descriptive statistics of the explanatory variables used in the right-hand side of equation (9) and (10). Patients receiving specialised services are more likely to be male and younger (probably mainly because infants are more likely to require specialised activity, 16% of them at birth), to have multi-episode spells, and to

[5] Alternatively the cost of the provider spell can be based on the most expensive FCE in the spell or by taking the first FCE in the spell. Results are not sensitive to these alternative calculations, and are reported in full in Daidone & Street (2010).

have been transferred between hospitals. The diagnostic characteristics were constructed using ICD10 codes, so there might be some overlap with the codes used for the definition of specialised services. However, other than a very small correlation between obesity and morbid obesity services, we found no correlation between the other services and the patients' characteristics.

# 6. Results

## 6.1 Specialist markers

Rather than reporting the coefficients for every specification[6], in Table 4 we report the predicted percentage increase in costs for specialised services for the four estimated equations with the dependent variable first in linear and then log form. The specialised markers where estimates are statistically significant (>1%) appear in bold. There are some general issues to note.

- The level of significance for most specialist markers tends to be consistent across specifications. This means that we can be confident in interpreting (i) a significant positive coefficient as indicating that the specialist marker has a significant positive impact on cost and (ii) a non-significant coefficient as indicating no significant impact of the marker on costs. Thus significance is not due to incorrect model specification.
- The size of the predicted effect is lower in the equation (10) than in equation (6). The difference is due to the fact that full specification includes patient characteristics and hospital effects and their inclusion partially purges the effect of specialised services.
- Comparing the linear and log forms of the same equation, sometimes the magnitude of the predicted effect is higher and sometimes lower for the linear specification. The direction in which effects differ will relate to how costs are distributed for patients with the specialist marker in question.

In the case of every specialised marker the predicted effects are larger in equation (6) than in (8). This is because equation (6) ignores the influence on costs associated with the hospital in which care was delivered and, consequently, this specification risks over-estimating the impact of the receipt of specialised services on an individual's cost.

- For the colorectal specialist marker the difference between the estimates is negligible. This implies that the higher costs observed for patients who receive specialised colorectal care are not due to the hospital in which they were treated. This would suggest that, for these services, there is little variation among hospitals in the costs of specialised care for these types of patients.
- For other types of treatment, though, the predicted effects differ more markedly, most obviously for spinal, children's and rheumatology specialised services. The differences imply that higher costs are not due solely to whether the patient received specialised services but are also related to the hospital that provided the care. It could be that some hospitals systematically attract more patients with other characteristics that explain higher costs; it could be that these hospitals

[6] These are available in Daidone & Street (2010).

exert less cost control and are less efficient. Consideration of the other specifications will help disentangle these explanations.

Compare equation (6) with equation (9), where the latter specification ignores the clustering of patients within hospitals. This comparison allows us to assess what impact there might be on the coefficients of the specialised markers of taking into account other patient characteristics that might explain costs. Again concentrating only on those specialist markers that are significant, three patterns emerge:

- For some specialist markers there is very little difference between the two estimates. This is the case for the cancer and colorectal markers and implies that patient characteristics do not explain variation in patient costs over and above the influence of the specialist marker.
- For other specialist markers the estimates in equation (9) are lower than those from equation (6). This is so for spinal, neurosciences, cystic fibrosis and children's specialist services. The differences are because patients receiving these types of specialist care also have other characteristics that drive their higher costs. Equation (6) ignored these characteristics and, consequently, their influence was partially captured by the specialist markers.
- In contrast, the estimates for some markers are higher in equation (9) than in equation (6), as seen for rheumatology and orthopaedic specialist markers. This implies a negative correlation between receipt of these specialised services and those patient characteristics that drive costs. At first sight this might seem surprising but consider again the descriptive statistics for these characteristics reported in Table 3. Those who received specialised services are not always more likely than those who did not to have the potentially cost increasing characteristics.

Finally, there are puzzling results for three of the specialist markers.

- The significance level for cardiology varies according to model specification. In the linear form of equation (6) and in every log specification, cardiology patients who receive specialised care are found to have significantly higher costs than those who do not. In the other linear models, the predicted effects are not significant. These unstable results may be due to the construction of cardiology HRGs, whereby many are populated almost entirely by patients who received a specialised services. This is particularly true for patients receiving coronary artery bypass grafts, value procedures, and percutaneous coronary interventions.
- For infectious diseases and vascular services, the specialist markers are significant in (some of) the linear models but insignificant in the log models. This instability may be due to the relatively small number of patients classified as having these specialised services.

## 6.2 Hospital effects

As would be expected, the vast majority of the variance in patient costs is due to their different characteristics rather than to the hospital in which they are treated – *rho*=0.017 for the estimated equation (10).

Nevertheless, there are differences among hospitals, and the random effect captures the hospital's influence on costs over and above the influence of the other patient-level variables accounted for in the model. Consequently these random effects can be interpreted as measures of each hospital's cost efficiency. The cost of a typical patient in a hospital with a relatively large random effect is higher than the cost of a comparable patient treated in a hospital with a lower random effect. Interpretation of these random effects as measures of relative cost efficiency is conditional upon having properly accounted for other factors that might explain variation in patient costs.

Consider equations (6) and (10) both of which account for the clustering of patients in hospitals. In equation (6) we account for the HRG to which the patient is allocated and whether or not they received specialised care. Thus the random effects are not contaminated by these factors. But they might be contaminated by other patient characteristics if there are systematic differences in the types of patients that hospitals treat that are not already captured by HRGs and the specialised markers. Equation (10) accounts for these characteristics and, therefore, the random effects from this specification provide a more accurate indication of each hospital's relative cost efficiency than does equation (6).

That said, there is little practical difference between these two sets of random effects, the spearman rank correlation amounting to 90% for the linear models and 95% for the log models. This implies that patients do not differ systematically across hospitals in terms of the set of characteristics that are accounted for in equation (10).

Hospitals can be ranked according to their cost efficiency as captured by the random effect, ordered from those with the lowest average costs for their patients to those with the highest average costs. However, ranking is sensitive to linear and log forms of the model, the correlation between the random effects for the two versions of equation (10) amounting to 75%. Distributions of these random effects are shown in Figure 2. As would be expected, the distribution is less extreme for the log specification. For a handful of hospitals there are quite large movements but for most hospitals the ranking is little changed.

## 7. Conclusions

Unless the basis for the claims that specialist hospitals require top-up payments can be established, the financial incentives introduced by prospective payment to encourage cost reducing behaviour will be diluted. In this paper we have explored the basis for these claims by assessing the marginal costs associated with receipt of specialised care for all patients treated in English hospitals during 2008/09.

For some specialised markers our analysis suggests that costs are indeed higher than for other patients allocated to the same HRG. The implication for PbR is patients with these markers might be paid an additional top-up over and above the tariff associated with the HRG to which they are allocated. The size of additional top-up might be up to the percentage increase in costs as in Table 4. Of these estimated effects, equation (8) is the preferred model on which top-up payments should be based, this model accounting

for clustering of patients within hospitals, but ignoring other patient characteristics that may not be adequately captured by the HRG to which each patient is allocated. The top-up payments would be equivalent to the predicted effect from either the linear or log specifications. The services meriting top-ups are cancer (13-18% higher payment than for other patients in the same HRG), spinal (28-31%), neurosciences (23-24%), cystic fibrosis (26-38%), children's (15-20%), rheumatology (13-25%), colorectal (18-21%) and orthopaedic (20-21%). Additional payments would not be made in the presence of the other specialised care markers, there being insufficient evidence to suggest that the costs associated with these types of specialised care drive higher costs. Specialised services for cardiology require further investigation.

Given the sensitivity of results to the linear and log specifications, in further work we intend to estimate generalized linear models (GLM). This would allow use to specify: i) a distribution that reflects mean - variance relationship, and ii) a link function between linear part $X\beta$ and mean $\mu = E(y|X)$. With GLM variance structure we would be able to accommodate skewness and related issues via variance-weighting rather than transform/retransform methods.

The amount of additional top-up received by each hospital will depend on the volume and type of their patients who receive specialised care. This would ensure that the payment policy relating to specialised services is consistent with the overall policy of Payment by Results. Currently, top-up payments are paid only to specialist orthopaedic hospitals and children's hospitals. The top-up for the former hospitals currently amounts to 30%, little different to the estimates from our analysis. But the top-up for children's hospital currently amounts to 78%. Clearly, revising the basis for top-ups implies that these hospitals would face reduced income, all else equal. Children's hospitals are already alive to this prospect and have been petitioning their local MPs to fight their cause as this recent exchange in the House of Commons, reported in Hansard, illustrates:

Tony Lloyd (Manchester Central) (Lab): "The Secretary of State will know that his Department has written to specialist children's hospitals threatening to withdraw the top-up moneys that are recognised as important in treating the most critically ill children. That is outrageous and seems to run counter to the Government's commitment not to cut funding."

The Secretary of State for Health (Mr Andrew Lansley): "I am afraid that I have to correct the hon. Gentleman. We are not withdrawing specialist top-up payments; the Department has acted on the basis of a review conducted by the University of York which was initiated by the Opposition Front Bench team's predecessors when they were in government."

The views of conference delegates on the issues raised in this paper would be appreciated so that payment policy can be informed by robust evidence rather than political lobbying.

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## Appendix 1 - Mapping of Reference Costs to HES records

In making their cost returns to the English Department of Health hospitals report five pieces of cost information for each HRG ($h$) in each of their specialties. So, for any given specialty, $j$, each hospital $k$ will report:

- Average cost per day case in HRG $h$: $c^{d}_{hjk}$
- Average cost for elective patients in HRG $h$ with a length of stay below the HRG-specific trimpoint value: $c^{e}_{hjk}$
- Excess *per diem* cost for an elective patient in HRG $h$ who stays in hospital beyond the HRG-specific trimpoint: $ex^{e}_{hjk}$
- Average cost for non-elective (including maternity, baby or a transfer) patients in HRG $h$ with a length of stay below HRG-specific trimpoint value: $c^{n}_{hjk}$
- Excess *per diem* cost for a non-elective patient in HRG $h$ who stays in hospital beyond the HRG-specific trimpoint $ex^{n}_{hjk}$

Trimpoints are defined for length of stay outliers in each HRG according to whether the patient was admitted as an elective or non-elective. We define $t^{e}_{h}$ as the elective trimpoint in days and $t^{n}_{h}$ as the nonelective trimpoint for HRG $h$.

The costs provided by each hospital are assigned to each patient record in HES, according to whether the patient was a day case $(a^{d})$, elective $(a^{e})$ or non-elective $(a^{n})$ admission and how long each patient stays in hospital, as follows:

- Day case: $if \quad a^{d}_{ihjk} \rightarrow c^{d}_{hjk}$
- Elective with length of stay at or below the elective trimpoint: $if\,(a^{e}_{ihjk}, L_{ihjk} \leq t^{e}_{h}) \rightarrow c^{e}_{hjk}$
- Elective with length of stay above the elective trimpoint: $if\,(a^{e}_{ihjk}, L_{ihjk} > t^{e}_{h}) \rightarrow c^{e}_{hjk} + \left[ ex^{e}_{hjk} \times (L_{ihjk} - t^{e}_{h}) \right]$
- Non-elective with length of stay at or below the non-elective trimpoint: $if\,(a^{n}_{ihjk}, L_{ihjk} \leq t_{h}) \rightarrow c^{n}_{hjk}$
- Non-elective with length of stay above the non-elective trimpoint: $if\,(a^{e}_{ihjk}, L_{ihjk} > t^{n}_{h}) \rightarrow c^{n}_{hjk} + \left[ ex^{n}_{hjk} \times (L_{ihjk} - t^{n}_{h}) \right]$

**Table 1: number of spells receiving specialised services**

| Service | # | | Service | # |
|---|---|---|---|---|
| No spec.Serv. | 10,620,999 | | Dermathology | 10,414 |
| Cancer | 13,915 | | Rheumathology | 356 |
| BMT | 1,034 | | Endocrinology | 6,985 |
| Haemoph. | 146 | | Respiratory | 189,844 |
| Womens | 22,406 | | Vascular dis. | 786 |
| Spinal | 4,089 | | Pain Manag. | 738 |
| Neurosc. | 30,556 | | Ear surg | 1,702 |
| Cystic Fibr. | 83,454 | | Colorect. | 6,761 |
| Renal | 360,826 | | Orthop. | 3,657 |
| Intestinal fail. | 2,325 | | Obesity | 7,744 |
| Cardiology | 125,983 | | Methabolic dis | 3,156 |
| Cleft Lip | 219,068 | | Ophtalmol | 6,341 |
| Infectious dis | 2,111 | | Haemoglobin | 141,170 |
| Liver | 33,102 | | >1 Spec. Serv. | 53,417 |
| Children | 201,514 | | Total | 12,154,599 |

**Table 2: Mean (SD) costs by type of activity**

| | Not specialized | Specialized | Total |
|---|---|---|---|
| Sum | 1364.6 | 1931.3 *** | 1436.1 |
| | (2045.7) | (3658.7) | (2319.7) |
| Max | 1206.9 | 1671.2 *** | 1265.5 |
| | (1707.0) | (3078.2) | (1940.5) |
| Epi1 | 1134.2 | 1523.8 *** | 1183.3 |
| | (1568.2) | (2803.9) | (1776.9) |

**Note:** *** 1% significant

**Table 3: Descriptive statistics of explanatory variables (st.dev. in parenthesis)**

| | Not spec | Spec | Tot | | Not spec | Spec | Tot |
|---|---|---|---|---|---|---|---|
| female1 | 0.576 | 0.450 | 0.560 | alcohol | 0.0170 | 0.00881 | 0.0160 |
| | (0.494) | (0.498) | (0.496) | | (0.129) | (0.0934) | (0.125) |
| age | 51.79 | 48.97 | 51.44 | smoke | 0.0363 | 0.0391 | 0.0367 |
| | (24.02) | (26.76) | (24.40) | | (0.187) | (0.194) | (0.188) |
| urban1 | 0.819 | 0.815 | 0.818 | obesity | 0.00698 | 0.0143 | 0.00791 |
| | (0.385) | (0.388) | (0.386) | | (0.0832) | (0.119) | (0.0886) |
| episodes | 1.112 | 1.149 | 1.117 | allergy | 0.0275 | 0.0213 | 0.0267 |
| | (0.415) | (0.583) | (0.440) | | (0.164) | (0.144) | (0.161) |
| emerg | 0.376 | 0.248 | 0.360 | diabetes | 0.0782 | 0.0677 | 0.0769 |
| | (0.484) | (0.432) | (0.480) | | (0.269) | (0.251) | (0.266) |
| die | 0.0140 | 0.0282 | 0.0158 | hypertens | 0.170 | 0.131 | 0.165 |
| | (0.118) | (0.165) | (0.125) | | (0.376) | (0.337) | (0.372) |
| tr_in_el | 0.0000394 | 0.000141 | 0.0000522 | haemorr | 0.00385 | 0.00862 | 0.00445 |
| | (0.00627) | (0.0119) | (0.00723) | | (0.0620) | (0.0924) | (0.0666) |
| tr_in_nonel | 0.0261 | 0.0415 | 0.0280 | histdis | 0.108 | 0.0930 | 0.106 |
| | (0.159) | (0.199) | (0.165) | | (0.310) | (0.290) | (0.307) |
| tr_out_el | 0.00479 | 0.00643 | 0.00500 | riskfact | 0.00731 | 0.00336 | 0.00681 |
| | (0.0691) | (0.0799) | (0.0705) | | (0.0852) | (0.0579) | (0.0822) |
| tr_out_nonel | 0.0112 | 0.0143 | 0.0116 | congmalf | 0.0102 | 0.0489 | 0.0151 |
| | (0.105) | (0.119) | (0.107) | | (0.101) | (0.216) | (0.122) |
| pregnancy | 0.107 | 0.00445 | 0.0941 | risk_phys | 0.000607 | 0.00134 | 0.000700 |
| | (0.309) | (0.0666) | (0.292) | | (0.0246) | (0.0366) | (0.0265) |
| drug | 0.00322 | 0.00239 | 0.00312 | risk_psysoc | 0.00383 | 0.00205 | 0.00361 |
| | (0.0567) | (0.0489) | (0.0557) | | (0.0618) | (0.0452) | (0.0600) |

## Table 4: Estimated predicted effects

| | Linear models | | | | Log models | | | |
|---|---|---|---|---|---|---|---|---|
| Equation: | [6] | [8] | [9] | [10] | [6] | [8] | [9] | [10] |
| Cancer | **0.2173** | **0.1842** | **0.2168** | **0.1879** | 0.1445 | 0.1320 | 0.1459 | **0.1339** |
| BMT | -0.0551 | -0.1045 | -0.0499 | -0.0897 | -0.0178 | -0.0331 | -0.0126 | -0.0240 |
| Haemophilia | -0.0886 | -0.1435 | -0.1839 | -0.2022 | -0.1593 | -0.1644 | -0.1139 | -0.1060 |
| Womens | -0.0031 | -0.0192 | -0.0071 | -0.0157 | 0.0310 | 0.0183 | 0.0214 | 0.0170 |
| Spinal | **0.3231** | **0.2755** | **0.3043** | **0.2729** | **0.3982** | **0.3117** | **0.3691** | **0.2932** |
| Neurosciences | **0.2791** | **0.2286** | **0.2051** | **0.1691** | **0.2490** | **0.2448** | **0.2002** | **0.1962** |
| CysticFibrosis | **0.3965** | **0.3792** | **0.3499** | **0.3347** | **0.2694** | **0.2580** | **0.2113** | **0.1984** |
| Renal | -0.1118 | -0.1117 | -0.0803 | -0.0868 | 0.0127 | 0.0150 | 0.0357 | 0.0360 |
| IntestinalFailure | -0.0074 | 0.0017 | -0.0253 | -0.0196 | 0.0715 | 0.0732 | 0.0453 | 0.0465 |
| Cardiology | **0.1382** | 0.0007 | 0.0567 | -0.0600 | **0.2625** | **0.1976** | **0.1875** | **0.1287** |
| CleftLip | -0.0171 | -0.0423 | -0.0032 | -0.0144 | 0.0161 | 0.0026 | 0.0099 | 0.0033 |
| InfectiousDiseaes | **0.2644** | **0.2129** | **0.2312** | **0.2049** | -0.0365 | -0.0669 | -0.0594 | -0.0808 |
| Liver | 0.0978 | 0.0754 | 0.0809 | 0.0637 | 0.0529 | 0.0442 | 0.0294 | 0.0293 |
| Children | **0.2804** | **0.1997** | **0.2524** | **0.1742** | **0.1748** | **0.1457** | **0.1158** | 0.0911 |
| Dermatology | 0.0087 | -0.0087 | 0.0135 | -0.0037 | -0.0658 | -0.0715 | -0.0638 | -0.0707 |
| Rheumatology | **0.1827** | **0.1298** | **0.2019** | **0.1618** | **0.3332** | **0.2477** | **0.3503** | **0.2720** |
| Endocrinology | 0.0451 | -0.0071 | 0.0517 | 0.0110 | 0.0404 | 0.0094 | 0.0451 | 0.0196 |
| Respiratory | 0.0458 | -0.0381 | -0.0059 | -0.0743 | -0.0905 | -0.1214 | -0.1322 | -0.1518 |
| VascularDiseases | **0.2461** | **0.2112** | 0.1981 | 0.1753 | 0.1269 | 0.1015 | 0.0812 | 0.0593 |
| PainManagement | 0.1878 | 0.1902 | 0.2278 | 0.2200 | -0.2563 | -0.2100 | -0.2315 | -0.1965 |
| EarSurgery | 0.0570 | -0.0006 | 0.0847 | 0.0183 | 0.0794 | 0.0441 | 0.0995 | 0.0555 |
| Colorectal | **0.2136** | **0.2105** | **0.2181** | **0.2150** | **0.1758** | **0.1813** | **0.1720** | **0.1791** |
| Orthopaedic | **0.2443** | **0.2130** | **0.2581** | **0.2248** | **0.2550** | **0.1997** | **0.2925** | **0.2283** |
| MorbidObesity | -0.0268 | -0.0075 | -0.0438 | -0.0106 | 0.0271 | 0.0329 | -0.0100 | 0.0157 |
| MetabolicDisorders | 0.0215 | -0.0155 | 0.0506 | 0.0023 | -0.3371 | -0.3043 | -0.3252 | -0.3039 |
| Ophtalmology | 0.0800 | 0.0570 | 0.0923 | 0.0784 | 0.1194 | 0.0741 | 0.1327 | 0.0923 |
| Haemoglobinopaty | 0.0128 | 0.0031 | 0.0140 | 0.0131 | -0.1042 | -0.1112 | -0.0998 | -0.1013 |

**Figure 1 Distribution of costs**

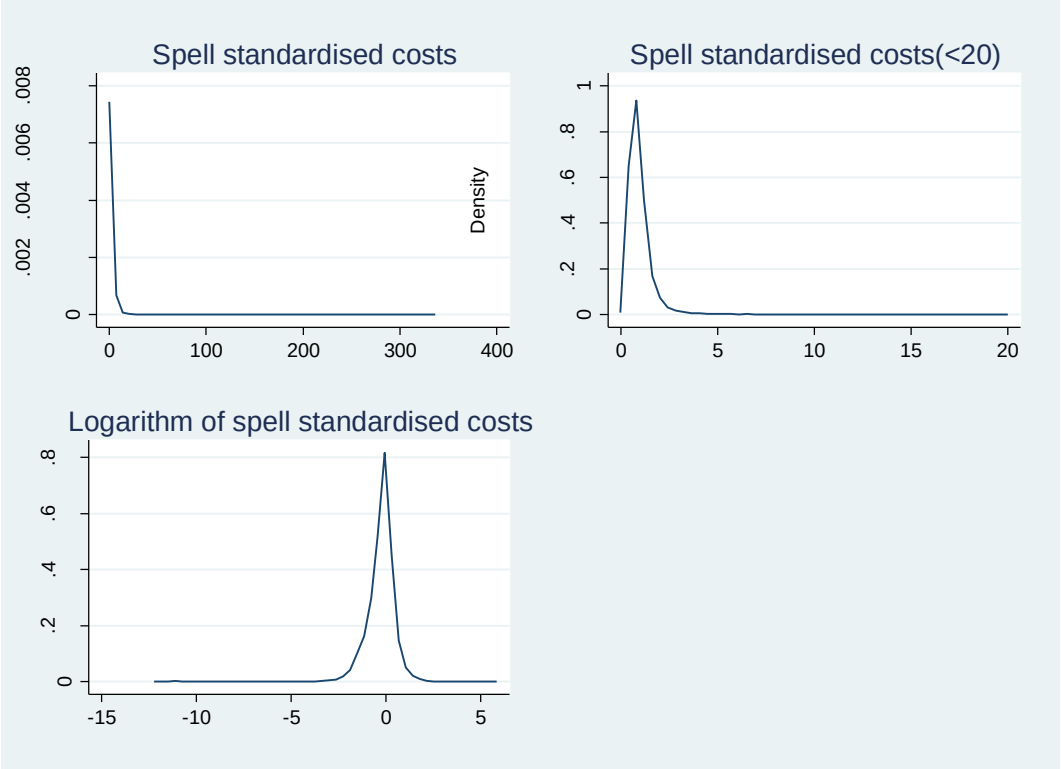


**Figure 2 Distribution of random effects**