Examining cost variation across hospital departments – a two-stage multilevel approach using patient level data

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Abstract

Studies of hospital efficiency seldom lead to changes in practice, partly because recommendations are unspecific or results are not seen as robust. We describe a method to compare hospital costs that utilises patient-level data. We perform a two-stage analysis in which we first consider factors that explain costs among patients and then across hospital departments. We illustrate our approach by examining the costs and characteristics of almost one million patients admitted to 136 English obstetrics departments in 2005/6. We identify those departments with significantly higher costs that need to take action.

Key words
Hospital efficiency, multilevel models, prospective payment, obstetrics

1 Introduction

In general health care organisations face limited competitive pressures that would otherwise encourage them to innovate and adopt cost minimising behaviour. Competitive behaviour may be even less in evidence if health care is publicly funded or in situations where organisations enjoy a geographical or specialist monopoly of supply (Bilodeau et al., 2000). When competitive pressure is weak, there may be scope for better utilisation of resources and reductions in cost. But in the absence of competition, a regulatory authority or policy maker might be tasked with devising incentives that encourage organisations to reduce their costs. These incentives might be relatively high-powered, particularly if backed up by financial rewards, or lower-powered, such as benchmarking or comparative efficiency analyses.

Many countries have introduced some form of prospective funding to pay for hospital care, whereby hospitals are paid according to the number and type of patients they treat and are unable to influence the price they face (Busse et al., 2006). This creates clear financial incentives to reduce costs: hospitals that provide care at a cost below the price will make a profit; those providing relatively expensive care will make a loss. Such financial arrangements require a means of classifying patients to a limited set of payment categories, and most countries use some form of Diagnosis Related Groups (DRGs) to achieve this. However the classification system used to differentiate between patients can never account for all cost variation, opening up the possibility that organisations claim for special treatment because their patients are somehow 'different' from those in other organisations. Specialist, teaching, or rural hospitals or those serving disadvantaged communities, for instance, might argue that, for whatever reason, they treat relatively more expensive patients within any payment category and in some countries such hospitals have been successful in securing additional funds on top of the DRG-based price (Department of Health, 2009, Flook, 2007, Danske Regioner et al., 2007, Epstein et al., 1990, Duckett, 1998, Brook, 2007). The danger is that, unless the basis for these claims can be established, financial incentives to encourage cost reducing behaviour will be diluted. At the extreme, with every hospital trying to influence the price it faces, prospective funding risks degenerating to cost-based reimbursement. By comparing costs across hospitals, the regulator can guard against this risk and many commentators have argued that, either alongside or instead of financial incentives, comparative performance assessment has a role to play in encouraging cost containment (Holmström, 1979, Shleifer, 1985).

This raises the question of how to conduct the comparative analysis and numerous studies have examined hospital costs or efficiency using techniques such as data envelopment analysis (DEA) or stochastic frontier analysis (SFA) (Worthington, 2004, Hollingsworth, 2008, Rosko and Mutter, 2008). These studies often rely on data reported at hospital level, the prime reason being that this is the usual form in which data are made available. However these standard means to perform the comparative assessment of hospitals present various drawbacks.

The most fundamental limitation is that it cannot be assumed that a common production function applies across all hospitals. Indeed the majority of hospitals, particularly non-specialist hospitals, house a range of different departments or specialties, each of which can be considered as having a distinct production function. It is difficult to capture these distinctive features in hospital-level analysis, especially when hospitals are heterogeneous with respect to their specialty mix. Any failure to observe and control for this heterogeneity will bias the comparative assessment.

Secondly, analysis restricted to hospital-level data runs into sample size problems in many contexts, particularly when considering countries with small populations or if comparing particular types of hospital (Olsen and Street, 2008). Although DEA is more robust to small sample sizes than SFA, even this technique progressively overestimates efficiency the smaller the sample size and the better specified the production model (Smith, 1997).

Thirdly, traditional DEA and SFA inefficiency analyses are based on the identification of the cost (or production) frontier of a group of organizations. Inefficiency is then calculated as the distance between each organizations' costs and the estimated cost possibility frontier. Generally both approaches need strong and non-testable assumptions about the model specification (Stone, 2002, Smith and Street, 2005), and this risks undermining the comparative exercise.

Fourthly, despite the proliferation of academic research, it has had limited influence on regulatory policy and its impact on hospital behaviour has been negligible (Hollingsworth and Street, 2006). Hospitals are multi-product organisations and, to take action, management needs to know in which part of the hospital the problems arise. Studies that consider the hospital as a whole offer limited insight into the source of higher costs or apparent inefficiency.

In previous work it has been argued that comparison of hospital departments (or specialties) is preferable to comparison of the hospital as a whole (Harper et al., 2001). This is because each particular department is more likely to be undertaking comparable activities, treating similar types of patients and, hence, applying a production technology similar to that in the same department in other hospitals (Jacobs et al., 2006). Thus comparing the same department across hospitals is more appropriate for both analytical purposes and for informing policy-makers and practitioners about how to respond to the findings. However, research that focuses on departments is uncommon because routine data, particularly on costs, are rarely available at this level. In this paper we seek to overcome this drawback by exploiting patient-level data, recognising that patients are clustered within departments.

The use of patient-level data offers further important analytical advantages, making it possible to exploit information about the characteristics of individual patients clustered within each department rather than characteristics aggregated or averaged across patients (Rice and Leyland, 1996, Rice and Jones, 1997).

In all probability the primary reason why costs vary across hospital departments is because each treats a different mix of patients. Most studies make allowance for expected differences in care requirements by differentiating patients using DRGs or variants thereof such as the Healthcare Resource Groups (HRGs) used in England. However, as mentioned, patients classified to the same DRG will still have different costs. This would not be a problem if this variation were random across hospitals, where it is a matter of chance whether any particular patient is more or less expensive than the average patient in the DRG to which they are classified. With sufficiently large volumes within each hospital, these differences among patients cancel out.

Problems arise if the differences across providers are systematic, with one type of hospital more likely to treat low-complexity patients and another treating more high-complexity patients even though they are classified to the same DRG. For example, specialist hospitals might attract more severe patients as compared with other hospitals because of their reputed excellence in providing such treatments; or hospitals located in deprived areas might serve more complex patients because of the lower health status of people living in these areas. By using patient-level data when making performance comparisons, it is possible to control for various personal and diagnostic characteristics over and above the DRG to which the patient is allocated (Hvenegaard et al., 2009).

Inferences about the variables of interest will also be more robust if estimation is based on individual rather than aggregated data because standard errors will be more precisely estimated (Rice and Leyland, 1996). Taking advantage of this, applications of multilevel models have become increasingly commonplace. However they have been little utilised in analysing the performance of healthcare organisations where it has been uncommon to exploit patient-level data. In this paper we exploit patient-level data and undertake a two-stage analysis of the variation in costs among patients and across departments. We first employ a fixed effects model to examine the characteristics of patients that explain their costs over and above the DRG to which they are allocated. We are also able to ascertain how much of the variation in patient costs is related to the department in which patients are treated, this being captured by the departmental fixed effects. These fixed effects may be contaminated by heteroscedasticity so, in the second stage of our analysis, we employ an estimated dependent variable (EDV) model in order to explore the reasons for departmental-level variation in costs. This approach avoids the contentious problem of estimating an efficiency frontier as necessitated if applying either DEA or SFA (Stone, 2002, Smith and Street, 2005). Variation in costs across departments may be due to specific 'environmental' or unavoidable factors that influence costs that which are beyond departmental control. We show how to control for these factors and standardise for departmental characteristics. This allows us to generate an indicator of the comparative costs of each department purged of the influence of patient characteristics and unavoidable cost constraints.

We illustrate the technique using data for almost one million patients admitted to all 136 obstetrics departments in England during 2005/6. We assess three main questions. Firstly, to what extent are costs explained by the characteristics of patients admitted to these departments? Secondly, after controlling for patient characteristics, why do some obstetrics departments have higher costs than others? Thirdly, after controlling for patient and departmental characteristics, which departments still have significantly higher costs than others?

We provide a brief rationale for our focus on obstetrics care in section two, followed by a description of our data in section three. Our econometric approach is described in section four followed by results in section five. We draw conclusions in section six.

2 Obstetrics care in the English NHS

The National Health Service (NHS) in England is funded from general taxation and free at the point of use. Every NHS patient must register with a general practitioner

(GP), and patients require a referral from their GP in order to be admitted to hospital, except for emergency and maternity patients. As regards the latter, women usually deliver in the hospital where they receive antenatal care, with the GP organising antenatal classes and post-natal care. We focus on the hospital component of this care pathway, considering the costs of care in obstetrics specialties to illustrate our analytical technique.

We chose obstetrics for a number of reasons. First, obstetrics counts for a large proportion of NHS activity. Almost 8% of all hospital patients in 2005/6 were admitted to the obstetrics department, and the majority of hospitals (86%) provide an obstetrics service.

Second, there is large variation in costs across obstetrics departments. This is illustrated in figure 1 which shows that the average cost of treating an obstetrics patient varies across departments from £500 below the national average to £1000 above. Also highlighted in figure 1 are two specialist hospitals, Liverpool Women's and Birmingham Women's, with average costs £200 below and £150 above the national average respectively. These hospitals are highlighted to show what impact accounting for factors that influence costs might have on conclusions about comparative performance. Understanding what factors are responsible of such variation in costs is of crucial importance for hospital managers since from 2003/4 all hospitals in England have been progressively subject to a form of prospective funding known as Payment by Results (PbR) (Department of Health, 2006). Under PbR hospitals are paid a fixed price for each type of patient treated, with price based on the national average cost (Street and Maynard, 2007). Therefore, departments producing services at higher costs than the national average will suffer financial losses.

Third, it is highly unlikely that variations in cost are due to hospitals being selective about whom they admit or are due to patients selecting specific hospitals. The first possibility is ruled out because English hospitals are prohibited from advertising and cannot be selective about who they treat: access is based solely on clinical need (Department of Health, 2008a). Selection by patients is also less likely in obstetrics than for other specialities, with those requiring maternity care generally preferring to be admitted to hospitals close to their home (Propper et al., 2006, Propper et al., 2007).

Finally, there are analytical advantages to focussing on obstetrics rather than other hospital departments. For one thing, there is a limited set of HRGs to which obstetrics patients are allocated: the majority (96%) of activity is confined to twelve HRGs (chapter N, comprising neonatal, maternity and antenatal care). Table 1 shows the distribution of activity in obstetrics departments according to HRGs in the N chapter, together with summaries of cost. Compared to specialties that treat a more diverse set of patients, this should ensure limited heterogeneity in the production process across obstetrics departments.

The analytical task is also simplified because most patients (98%) admitted to obstetrics remain under the care of a single consultant during their hospital stay. In contrast, this is the case for about 79% of all patients admitted to hospital in England (Castelli et al., 2008). The implication is that, more so than in other hospital specialties, activity in obstetrics departments is reasonably self-contained. This helps ensure that the costs of care are borne solely and fully by the obstetrics department, rather than reflecting joint production with other specialties.

2 Data

We analyse the hospital episode statistics (HES) for all patients discharged from an English obstetrics department in 2005/6. HES comprise individual patient records – defined as a Finished Consultant Episode (FCE) – about every NHS patient admitted to hospital in England. 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).

From an initial population of 1,009,747 obstetrics patients the final sample used in our analysis is reduced to 951,277 after dropping patients for the reasons detailed in Appendix 1. Our main analysis considers all patients admitted to obstetrics, while a supplementary analysis focuses only on those admitted for maternity care, these being patients allocated to HRGs N06-N11. The latter analysis allows us to assess whether conclusions about costs across departments are sensitive to what activity is considered.[i]

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 (including maternity) HRG in 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 these 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 detailed in Appendix 2.

For obstetrics departments, variation in patient level cost is illustrated in Figure 1, where each vertical set of points shows the cost of all patients in each obstetrics department. Variation is also evident when considering the costs only for those admitted for a delivery, as shown in figure 2.

The most common explanation that hospitals offer for their higher costs is that they treat different types of patients to their counterparts. We consider various patient characteristics that might explain variation in costs. We construct a set of dummy variables specifying the HRG to which the patient is allocated (see Table 1), with the HRG for a normal delivery (N07) being the reference category.[ii] We also consider the patient's age, the income deprivation of the area where the patient lives and a set of variables specific to obstetrics care, namely the number of babies delivered, birth weight, and whether or not the baby was still-born. Finally we construct a set of diagnostic and procedural variables, including counts of diagnoses and operations performed and dummy variables which capture the most frequently recorded diagnostic characteristics that might explain costs over and above the HRG to which the patient is allocated. Table 2 reports the ICD-10 codes used to construct these variables and the number of obstetrics and maternity patients to which they apply. Descriptive details of the explanatory variables for all obstetrics patients and the maternity sub-sample are shown in table 3.

Part of the variation in costs across obstetrics departments may be due to the characteristics of the departments themselves. Descriptive statistics of department variables we consider are provided in Table 4. We consider the number of patients treated as a measure of departmental size, and assess whether larger departments have lower costs. Costs may also be driven by the size and composition of the staffing complement, which we capture as an index of the number of whole time equivalent obstetricians, gynaecologists and midwives per 100 patients. This index weighs staff of different types according to their respective wages.[iii]

We examine the impact of insurance contributions per birth on variation in departmental costs. These contributions are a significant proportion of costs incurred in obstetrics departments, with each department's contribution based on staffing levels, number of births, claims history and risk management strategies.[iv] We also consider variables describing the hospital in which the department is located, including whether it has a teaching function, a neonatology department operating as a distinct unit apart from the obstetric department, and how many sites the obstetrics department is split over, if any. We also take into account the quality of clinical coding by measuring what proportion of the hospital's total caseload lacks sufficient coded data to be apportioned to any HRG (Healthcare Commission, 2007).

Arguably all these departmental variables are within the control of the department, if only in the short run. Hospitals have (at least some) discretion about their scale of operation, their staffing complements, and the hospital's configuration. They are also able to influence their insurance contributions to some extent by improving their risk management strategies and can improve their coding of HES data. While these variables might explain variation in costs, they do not represent unavoidable constraints on their ability to control costs, at least not in the long term. Consequently it would not be legitimate to control for these factors in a performance analysis (Giuffrida and Gravelle, 2001, Smith and Street, 2005).

However, English hospitals do face unavoidable constraints that impact on their production costs and that are outside their control. These constraints are recognised by the English Department of Health which makes top-up payments to hospitals in more expensive parts of the country to take account of the differential prices of labour and capital inputs over which these hospitals have little control (Mason et al., 2009). These top-up payments are based on the so-called the Market Forces Factor (MFF) index which captures geographical variation in the cost of labour, buildings and land across England. We use this input price index to control for these unavoidable constraints when comparing costs across obstetrics departments.

4 Methods

Our objective is to analyse the variation in costs across departments after taking account of differences in the patients they treat and unavoidable factors that might affect departmental costs but that are beyond their control. To do this, we perform a two stage analysis. First we regress patient costs against a set of patient characteristics that might explain their costs. From this equation we obtain each department's average cost purged of the influence of the characteristics of their patients. Second we investigate variations in these average costs across departments using an Estimated Dependent Variable (EDV) model.

In the first stage we estimate a fixed effects model of the following form[v]:

$$c_{ij} = \boldsymbol{\beta}_h' \mathbf{h}_{ij} + u_j + v_{ij} \qquad (1)$$

Where c_{ij} is the cost for patient i in department j and $\mathbf{h}_{ij}$ is a vector of the variables capturing the HRG to which the patient is allocated and the other patient characteristics summarised in Table 3.

From equation (1) we obtain $\hat{u}_j$, the departmental fixed effect, which can be interpreted as a measure of relative departmental performance after allowing for differences in patient characteristics (Hauck et al., 2003, Bhalotra and Zamora, 2008). Positive values indicate that the average cost of patients in the department in question is above the national average.

Note that these fixed effects are not equivalent to the efficiency estimates derived from applying cross-sectional stochastic frontier models. A second-stage analysis of efficiency estimates is inappropriate because SFA models rely on estimation of an efficiency frontier in relation to which each organisation's efficiency is measured. This means that efficiency estimates are not independent observations, thereby invalidating the standard assumptions for regression analysis (Simar and Wilson, 2004). Instead, we avoid estimating a frontier and exploit the multilevel structure of our data to extract independently distributed departmental fixed effects.

Factors driving residual variation in costs across departments, as captured by these fixed effects, can be explored. To this end, the departmental fixed effects estimated in the first stage are regressed against a set of departmental variables in a second stage regression of the form:

$$\hat{u}_j = \delta_0 + \delta_1 z_j + \boldsymbol{\delta}_x' \mathbf{x}_j + \upsilon_j \qquad (2)$$

Where z_j captures unavoidable differences in input prices faced by providers in different parts of England as measured by the input price index and $\mathbf{x}_j$ is a vector of variables capturing departmental characteristics, summarised in Table 4.

In order to provide a picture of the obstetrics departments' relative performance, we examine the variation in their average costs after controlling for unavoidable differences in input prices and standardising for the departmental variables included in $\mathbf{x}_j$. This is achieved by indirect standardization:

$$\hat{u}_j^{is} = \hat{u}_j - \hat{u}_j^{z} \qquad (3)$$

$$\hat{u}_j^z = \hat{\delta}_0 + \hat{\delta}_1 z_j + \hat{\boldsymbol{\delta}}_x' \bar{\mathbf{x}}_j \tag{4}$$

Where $\hat{u}_j$ is obtained from equation (1) and $\bar{\mathbf{x}}_{jx}$ is the vector of departmental characteristics in equation (2) set to their mean. Standardization is performed in order to avoid omitted variable problems that might arise if the input price index, z_j, is correlated with $\mathbf{x}_j$ (O'Donnell et al., 2008). Finally, $\hat{\delta}_1$ and $\hat{\boldsymbol{\delta}}_x'$ are parameters estimated from equation (2).

We interpret $\hat{u}_j^{is}$ as a measure of relative departmental performance in controlling costs, purged of the effect of the characteristics of their patients and the input prices they face.

The two stage model described here is based on two main assumptions about the data generating process (DGP) that determines the observed cost, patient characteristics, and department characteristics in obstetrics departments. First, we assume separability between patient characteristics and input prices in the cost function of the obstetrics departments. This allows us to purge their influence from the departmental average cost. This is similar to the assumption made by Simar and Wilson in the solution they propose to the problem of non-independence of efficiency estimates from SFA and DEA models (Simar and Wilson, 2004).

Second, we assume that the obstetrics departments share the same cost function. This allows us to describe how departmental level variables influence department costs in the second stage and is required in order to identify what factors are responsible for the variation in average costs across departments. This is a fairly strong assumption for analysis at hospital level given the multiproduct nature of hospital activity. But we argue that the activity of hospital departments, such as obstetrics, is more homogeneous and, consequently, can be realistically considered as subject to the same underling production process.

The two-stage model we have specified borrows from the literature on EDV models that are widely applied in political analysis studies. Jusko and Shively and Lewis and Linzer discuss extensively the hypothesis under which EDV models involving a two stage approach are consistent and efficient (Jusko and Shively, 2005, Lewis and Linzer, 2005). In particular, heteroscedastic sampling errors in the estimated dependent variables might result in biased standard errors in the second stage analysis. Efron robust SE estimators are adopted, which are known to provide a suitable solution under this hypothesis.[vi]

Note also that the potential gains in efficiency from estimating a two-stage model in a single stage are modest when considerable information is available at the bottom level (Lewis and Linzer, 2005). In our study we have almost one million observations at patient level, with each department having no less than one thousand observations. This makes our two-stage procedure a valid analytical approach.

5 Results

5.1 Patient-level costs

Estimation results for the patient-level equations are presented in Table 5. Results for the full sample of obstetrics patients appear first. The first set of variables show the estimated cost for each HRG relative to the cost of a normal delivery (i.e. N07 HRG), after conditioning on the other covariates. Most of the neonatal HRGs (i.e. N03-N05) are less expensive than the reference HRG, N07, hence their negative values. The main reason is that neonatal care, particularly for more complex cases, is managed in dedicated neonatology departments in most hospitals. Thus, most of the neonatal care supplied in the obstetric departments is probably for relatively less complex cases. For maternity HRGs (N06, N08-N11) the estimates are little different to the mean costs (compared to N07) reported in Table 1.

The estimates show that costs are driven by patient characteristics over and above their HRG classification. The income deprivation of the area where the patient lives is associated with higher costs, a finding in line with evidence about the relationship between socioeconomic deprivation of the patient treated and the cost of treatment (Cookson and Laudicella, 2009). As would be expected, costs are higher the more babies each woman delivers, the more diagnoses recorded and the more procedures performed. As for the diagnostic markers, in particular pre-eclampsia/eclampsia and infections explain an economically relevant portion of the average cost of patients treated in obstetrics and diabetics also have higher costs. Conversely some patient conditions are associated with lower costs, the most economically relevant being the occurrence of abortion.

The second set of estimates in table 5 presents results when considering maternity patients only (i.e., patients assigned to HRGs N06-N11). Results are broadly similar to those for all obstetrics patients, unsurprisingly given that maternity patients comprise 47% of the total. But there are some notable differences. The baby's weight and mother's smoking behaviour are associated with lower costs. The former is an indicator of the baby's and mother's health, while the latter reflects the circumstance that mothers in better health are less likely to quit smoking during pregnancy, as shown in the economic literature (Rosenzweig and Schultz, 1983). Finally, it is notable that the occurrence of an infection is by far the most relevant determinant of high costs in maternity care, patients suffering infections costing £300 more to care for than those who do not. Table 3 shows that 2% of maternity patients are at risk of infections. Particularly if contracted after admission, investment in efforts to reduce the risk of infection might generate substantial cost savings.

While patient characteristics explain much of the variation on costs, they do not explain it all. After taking all these characteristics into account, there remains a high degree of unexplained variation in the average cost per patient across departments, as indicated by the value of *rho* in Table 5. When considering all obstetrics patients, 19% of the variation in costs occurs at department level rather than being due to observed characteristics of the patients within departments. For maternity patients there is a higher proportion of variance in costs among departments (*rho*=28%). We explore what drives this departmental variation in our second stage analysis.

5.2 Comparison of departmental performance

In our second stage analysis, we consider what influence departmental characteristics have over variance in $\hat{u}_j$. The fixed effects from estimating equation (1) for all obstetrics patients are highly correlated with those from maternity sample (r=0.87).

Table 6 reports results from the model in equation (2) for all obstetrics and for just maternity patients. There is some evidence of lower costs in obstetrics departments with higher volumes of activity, although this effect is not statistically significant when considering the maternity sample. Costs are also lower in the obstetrics department if the hospital has a separate neonatology unit, perhaps indicating better organisation of services. Finally, higher average costs are evident in departments that face higher input prices, although the effect is not significant in the maternity sample. Insurance contributions are not significant in explaining variations in costs among departments. This is not surprising given that the burden of these premiums is similar across all departments as reported in the descriptive statistics in Table 2. Nor are any of the other variables are found to be significant predictors of the variation in departmental costs.

After controlling for differences among departments in the type of patients they treat and in the input prices they face by applying equation (3), we order departments according to their average costs and report the 95% confidence intervals around their mean in Figure 4. Note that the shape of this distribution is little different from that shown in Figure 1, where departments were ordered simply on the basis of their unadjusted costs. Even after standardising for patient characteristics and differential input prices there are significant differences in average costs across obstetrics departments. At the extremes, departments have standardised costs more than £500 above or below the national average.

The impact of allowing for patient characteristics and input prices varies from department to department. This is evident for the two specialist hospitals, both of which rise up the ordering when allowance is made for these things in considering their costs of provision. Figure 5 shows the extent to which each department changes its average costs once patient characteristics and input prices have been taken into account. Each department is ordered on the basis of its standardised average cost from the least to most expensive, with the vertical line indicating its unadjusted cost. It is notable that even though expensive departments have relatively more complex patients or face higher input prices, their costs are still higher than in other departments once these differences have been accounted for. Thus, the position of departments with higher costs remains unchanged and any claims that these departments treat relatively more complex patients or face higher unavoidable costs can be discounted.

Finally we consider what impact focussing solely on maternity provision has on the ranking of obstetrics departments according to their standardised costs. Figure 6 ranks departments from the least to most expensive in the provision of obstetrics care after adjusting for patient case-mix and input prices. The vertical line extending from each departmental position on the obstetrics rank shows their ranking if maternity care services only are considered.. For some departments the re-ranking is quite substantial. However, for the most and least expensive obstetrics departments it makes no difference whether analysis is based on all obstetrics patients or just on the maternity sub-sample. Therefore there are a handful of obstetrics departments with significantly higher costs that cannot be explained by the types of patients they treat or the input prices they face. These departments are those where the regulator or hospital management should have greatest concerns about their efficiency.

5 Conclusions

By using patient-level data our analysis offers several contributions over other approaches to consideration of hospital costs or efficiency. The first advantage is that the researcher is not restricted to consideration of the hospital as the unit of analysis but can undertake departmental-level analysis. One of the main analytical problems with analysing hospitals is that each comprises a diverse range of specialties and any failure to account for the heterogeneous mixture of production functions within and across hospitals will undermine the comparative exercise. We argue that departments can be considered more homogeneous and, therefore, more comparable than hospitals and can be assumed to be subject to a common production function.

Second, we provide more insight into why costs vary from one patient to another, since we are able to account for a much broader range of patient characteristics than simply the HRG (or DRG) to which the patient is allocated. As expected, the patient’s HRG captures much of difference in the cost of treating different patients in obstetrics. However, we found that some diagnostic markers also contribute in explaining differences in costs over and above the HRG classification. Most striking here is that patients suffering an infection have substantially higher costs. These costs might be avoided if the risk of infection could be reduced.

Variation in costs over and above HRG classification may be indicative of some inadequacies with the HRG classification system, which has been revised since the time to which the data in this study refer. The new version 4 HRGs may be more successful at capturing variation in costs because the number of HRGs has been expanded considerably, from 665 to around 1400 HRGs overall. The number of maternity HRGs in version 4 has expanded from six to nine and an age split (at 18 years) has been introduced.

Third, the multilevel structure of patient-level data enables us to obtain a departmental fixed effect without resorting to stochastic frontier methods. Thus, we are not forced to make assumptions about the production or cost frontier and are able to investigate variations in our fixed effects in a second-stage analysis – a process that would be suspect if analysing variation in non-independently distributed efficiency estimates (Wang and Schmidt, 2002, Simar and Wilson, 2004). Our comparative analysis of departments’ costs is purged of the influence of heterogeneity in the characteristics of their patients and of the influence of differential prices paid for their inputs. After taking account of the effect of patient characteristics and input prices, substantial variation in the average cost per patient persists across departments. Higher average costs are evident in smaller obstetrics departments, departments in hospitals that lack a separate neonatology department and where differential input factor prices are higher.

Although we have controlled for an extensive set of patient characteristics and differences in input prices in our analysis, there may be further explanations as to why costs vary across departments that our analysis has been unable to account for. One possibility is that hospitals differ in their coding practice, to the extent that some provide better coded HES data than others. Our variable measuring coding quality was not significant however. Another possibility is that hospitals assess their costs in different ways, with differences likely to stem from how they have decided to apportion shared resources, such as doctors working across specialties, or hospital overheads, even though the Department of Health give detailed guidelines on common accountancy practice to be adopted. While this apportionment is problematic whatever costing system is in place (Jackson, 2001), it may have less impact in obstetrics departments, these being relatively self-contained, than for specialties that are more inter-linked with others. A further reason why costs might differ, of course, is that some obstetrics are simply better organised and more efficient than others. We have identified those obstetrics departments that have significantly higher costs than others and that need to take action to avoid financial losses under a prospective funding regime.

Table 1 Activity in obstetrics departments, by HRG

HRG		Patients	% of all obstetrics patients	Cost Mean	Cost SD
N01	Neonates - Died <2 days old	252	0.0%	716	329
N02	Neonates with Multiple Minor Diagnoses	972	0.1%	1,091	201
N03	Neonates with one Minor Diagnosis	6,236	0.7%	763	176
N04	Neonates with Multiple Major Diagnoses	30	0.0%	830	1,082
N05	Neonates with one Major Diagnosis	184	0.0%	777	713
N06	Normal Delivery w cc	20,847	2.2%	1,831	765
N07	Normal Delivery w/o cc	251,360	26.4%	1,126	526
N08	Assisted Delivery w cc	5,916	0.6%	2,240	907
N09	Assisted Delivery w/o cc	50,597	5.3%	1,483	463
N10	Caesarean Section w cc	19,072	2.0%	3,366	1,310
N11	Caesarean Section w/o cc	97,547	10.2%	2,350	834
N12	Antenatal Admissions not Related to Delivery Event	464,972	48.8%	647	461
Total N		917,985	96.4%	1,100	854
Other	All other HRGs	34,292	3.6%	771	
Total		952,277	100.0%	1,079	

Table 2 Obstetrics patients with particular diagnostic markers					
Label	**ICD-10 diagnosis codes**	**All obstetrics patients**		**Maternity patients**	
Pre-eclampsia and eclampsia	O14.0-O15.9	14,335	1.51%	9,124	2.05%
Haemorrhage	O2O.8 O20.9 O44.1 O46 O67 O72 O03-6.1&6	74,946	7.88%	42,220	9.51%
Diabetes	O24 R81 E1	17,995	1.89%	9,395	2.12%
Infection	O23 O44.1 O75.3 O86 R50 J22.X O03-6.0&5	27,258	2.87%	8,709	1.96%
Hypertension	O16 O11 I10	28,089	2.95%	8,551	1.93%
Obesity	E66	2,002	0.21%	947	0.21%
Smoker	Z72.0	19,597	2.06%	14,142	3.18%
Lifestyle risk factors	Z72.1 Z72.2 Z72.4&8&9 Z35.7 Z86.4 Z91.5 Z86.5	9,568	1.01%	6,406	1.44%
Abortion	O01 O02 O03 O04 O05 O06 O07 O08	7,408	0.78%	407	0.09%
Allergy	Z88	15,041	1.58%	10,150	2.29%
Past history of disease	Z85 Z86.0&1&2&3&6&7 Z87.4	8,556	0.90%	5,777	1.30%
Complications in past pregnancy	Z87.5 Z87.6	2,785	0.29%	1,804	0.41%
Perineal laceration	O70.2 O70.3	93,873	9.87%	93,386	21.03%

Table 3 Descriptive statistics of patients

	All obstetrics patients		All maternity patients	
	mean	Std_dev	mean	Std_dev
Cost	1088	849	1578	915
Age	28.09	6.92	28.82	6.42
Income deprivation index	0.177	0.134	0.170	0.132
Number of babies	0.405	0.509	0.840	0.416
Birth weight (1000g)	1.174	1.630	2.432	1.562
Delivered dead	0.002	0.043	0.004	0.060
Number of operations	1.120	1.429	2.348	1.212
Number of diagnoses	2.294	1.432	3.165	1.411
Pre/eclampsia	0.015	0.122	0.021	0.142
Haemorrhage	0.079	0.270	0.096	0.294
Diabetes	0.019	0.136	0.021	0.144
Infection	0.029	0.167	0.019	0.138
Hypertension	0.030	0.169	0.019	0.137
Obesity	0.002	0.046	0.002	0.046
Smoker	0.021	0.142	0.032	0.175
Lifestyle risk factors	0.010	0.100	0.014	0.119
Abortion	0.008	0.088	0.001	0.030
Allergy	0.016	0.125	0.023	0.149
Past disease	0.009	0.094	0.013	0.113
Complications in past pregnancy	0.003	0.054	0.004	0.064
Perineal laceration	0.099	0.298	0.210	0.407
Observations	952,273		445,339	

Table 4 Departmental descriptive statistics

	Mean	Std_dev
Number of patients (100s)	70.02	41.03
Insurance per birth (£)	545.15	17.08
Staff	99.64	48.39
Teaching status	0.15	0.36
Neonatology dept	0.51	0.50
Total sites	1.15	0.50
Coding quality	1.18	1.97
Input price index (x100)	112.40	8.60
Departments	136	

Table 5 First stage estimates

	All obstetrics patients			All maternity patients		
	coeff	se	t	coeff	se	t
N01 Neonates - Died <2 days old	-279.19	107.21	-2.60			
N02 Neonates with Multiple Minor Diagnoses	237.34	116.17	2.04			
N03 Neonates with one Minor Diagnosis	-184.02	100.08	-1.84			
N04 Neonates with Multiple Major Diagnoses	-186.20	419.53	-0.44			
N05 Neonates with one Major Diagnosis	-215.25	219.76	-0.98			
N06 Normal Delivery w cc	681.00	72.74	9.36	636.67	64.38	9.89
N08 Assisted Delivery w cc	1023.30	59.96	17.07	990.87	51.82	19.12
N09 Assisted Delivery w/o cc	308.75	19.09	16.18	316.33	18.91	16.73
N10 Caesarean Section w cc	2119.47	74.40	28.49	2070.30	75.21	27.53
N11 Caesarean Section w/o cc	1192.64	52.35	22.78	1191.64	52.11	22.87
N12 Antenatal Admissions	-303.82	38.92	-7.81			
F47 General Abdominal Disorders <70 w/o cc	-170.30	72.90	-2.34			
S33 Examination, Follow up and Special Screening	-338.14	58.46	-5.78			
M05 Upper Genital Tract Minor Procedures	87.37	112.01	0.78			
M11 Medical Termination of Pregnancy	-56.83	42.94	-1.32			
M14 Treatment of Fibroids, Menstrual Disorders, or Endometriosis	-253.08	49.81	-5.08			
All other HRGs	-1.75	59.06	-0.03			
Age	-1.31	1.24	-1.05	-3.43	1.66	-2.06
Age^2	0.04	0.02	1.93	0.08	0.03	2.66
Income deprivation index	36.18	8.56	4.23	33.47	10.51	3.19
Number of babies	72.98	36.35	2.01	119.90	20.88	5.74
Birth weight	-14.37	12.56	-1.14	-53.76	5.29	-10.17
Delivered dead	-26.71	52.67	-0.51	-55.07	36.06	-1.53
Number of operations	34.87	7.72	4.52	19.07	3.92	4.87
Number of diagnoses	24.69	5.57	4.43	22.61	3.20	7.07
Pre/eclampsia	299.40	20.94	14.30	359.27	26.60	13.50
Haemorrhage	21.25	12.88	1.65	51.25	15.06	3.40
Diabetes	51.40	14.45	3.56	75.98	13.08	5.81
Infection	185.45	16.59	11.18	303.26	27.67	10.96
Hypertension	17.24	13.97	1.23	40.66	26.58	1.53
Obesity	-56.16	29.90	-1.88	7.83	36.27	0.22
Smoker	15.62	24.12	0.65	-38.71	10.12	-3.82
Lifestyle risk factors	-16.86	25.78	-0.65	21.06	11.79	1.79
Abortion	-160.11	36.25	-4.42	64.45	38.04	1.69
Allergy	-51.23	14.02	-3.65	-33.41	6.67	-5.01
Past disease	-15.46	12.80	-1.21	-4.55	8.37	-0.54
Complications in past pregnancy	-62.98	33.37	-1.89	-37.10	22.05	-1.68
Perineal laceration	-41.06	8.39	-4.89	-30.64	5.64	-5.43
Constant	917.46	36.50	25.13	1077.45	31.23	34.50
Sigma_u	250.31			362.03		
Sigma_e	524.21			573.82		
Rho	0.1857			0.2847		
R-sq within	0.5675			0.5444		
R-sq between	0.5161			0.0558		
R-sq overall	0.5514			0.4739		
Patients	952,273			445,339		
Departments	136			136		

Table 6 Results of second stage estimates

	All obstetrics patients			All maternity patients		
	coeff	Se	t	coeff	se	t
Number of patients (100s)	-1.58	0.66	-2.39	-1.75	1.17	-1.50
Insurance per birth (£)	0.83	1.32	0.63	1.81	2.01	0.90
Staff	0.72	0.44	1.64	1.31	0.88	1.48
Teaching status	-65.54	53.77	-1.22	-5.69	97.65	-0.06
Neonatology dept	-111.23	42.71	-2.60	-160.57	64.70	-2.48
Total sites	50.64	46.88	1.08	37.60	53.63	0.70
Coding quality	-3.50	9.95	-0.35	-1.68	16.58	-0.10
Input price index (x100)	7.03	2.71	2.59	5.49	4.57	1.20
Constant	-1153.94	815.46	-1.42	-1564.25	1304.47	-1.20
R-sq	0.19			0.11		
Departments	136			136		

Figure 1: Average cost of obstetrics care, by department

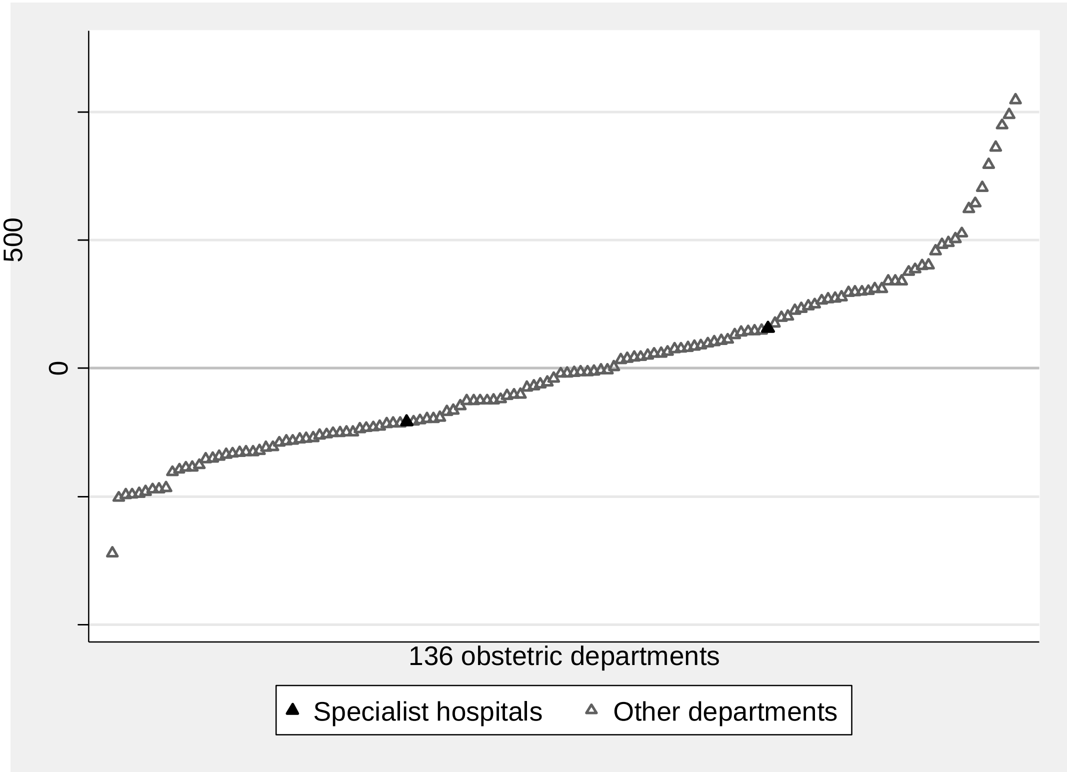


Figure 2: Patient costs by obstetrics department, all obstetrics patients

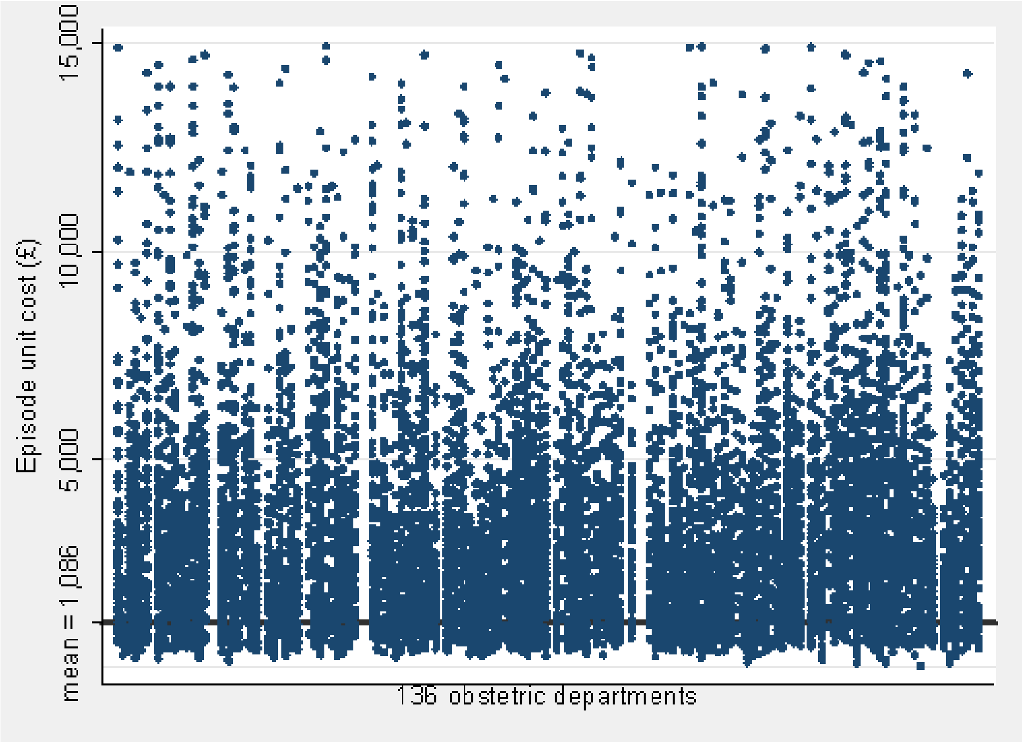


Figure 3: Patient costs by obstetrics department, maternity patients only

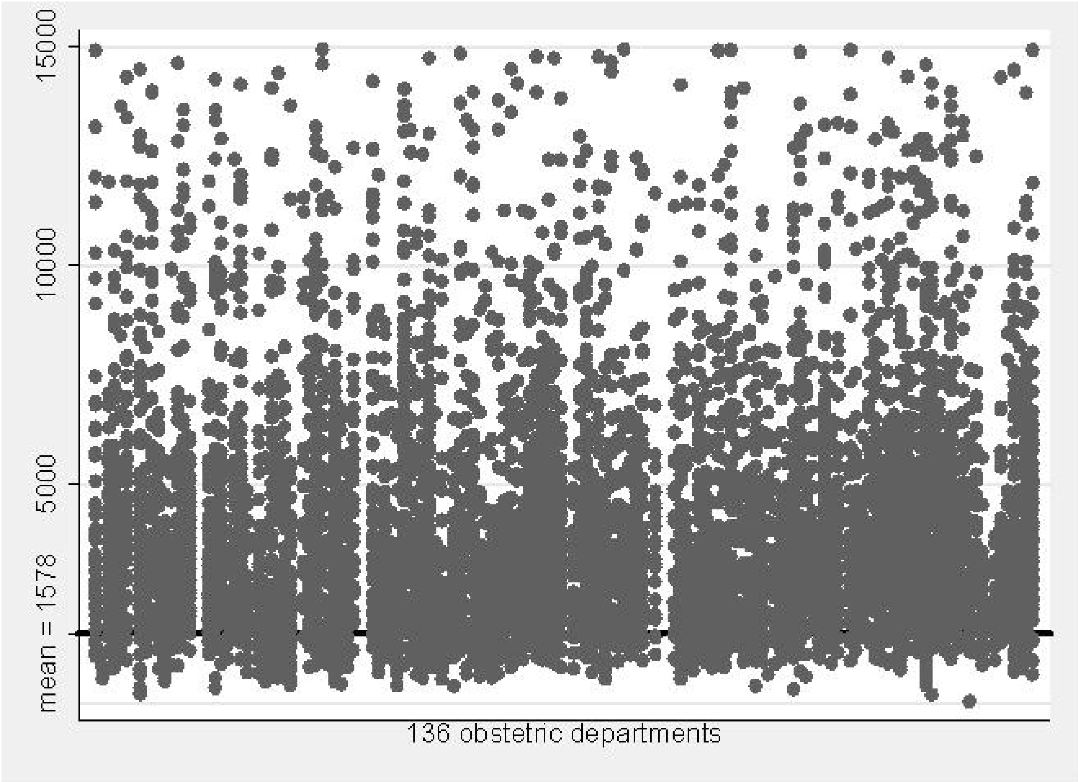

15000
10000
5000
mean = 1578
136 obstetric departments

Figure 4 Standardised average costs of obstetrics care and 95% confidence intervals, by department

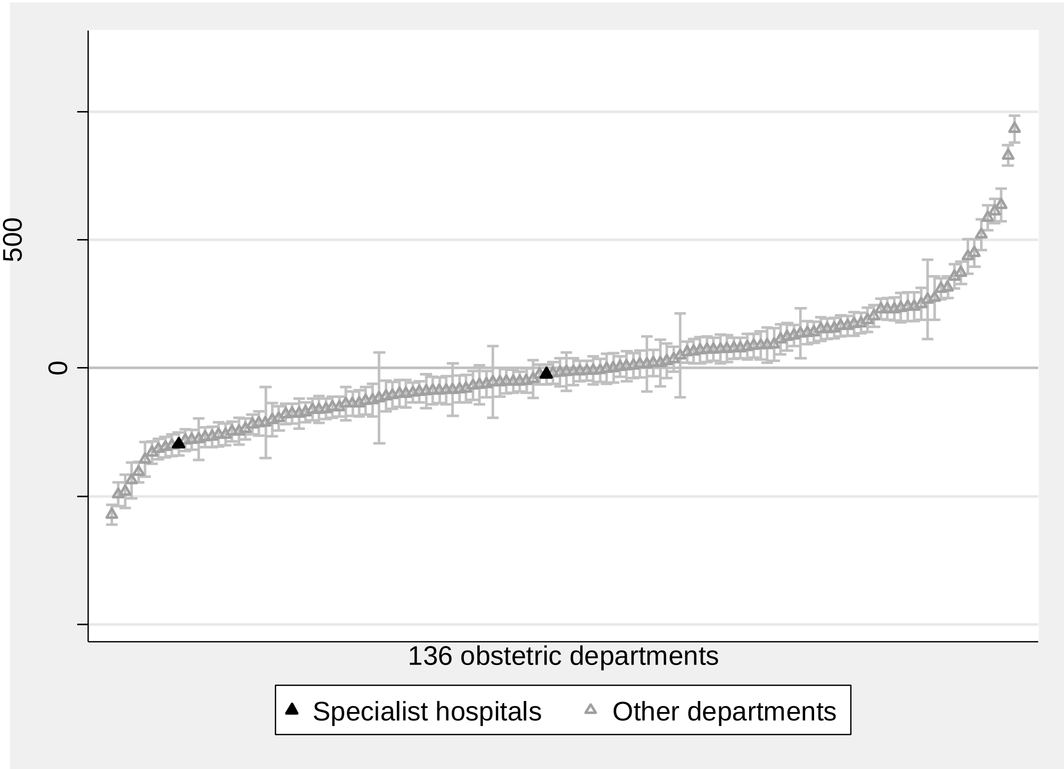


Figure 5 Comparison of standardised and unadjusted average costs, by department

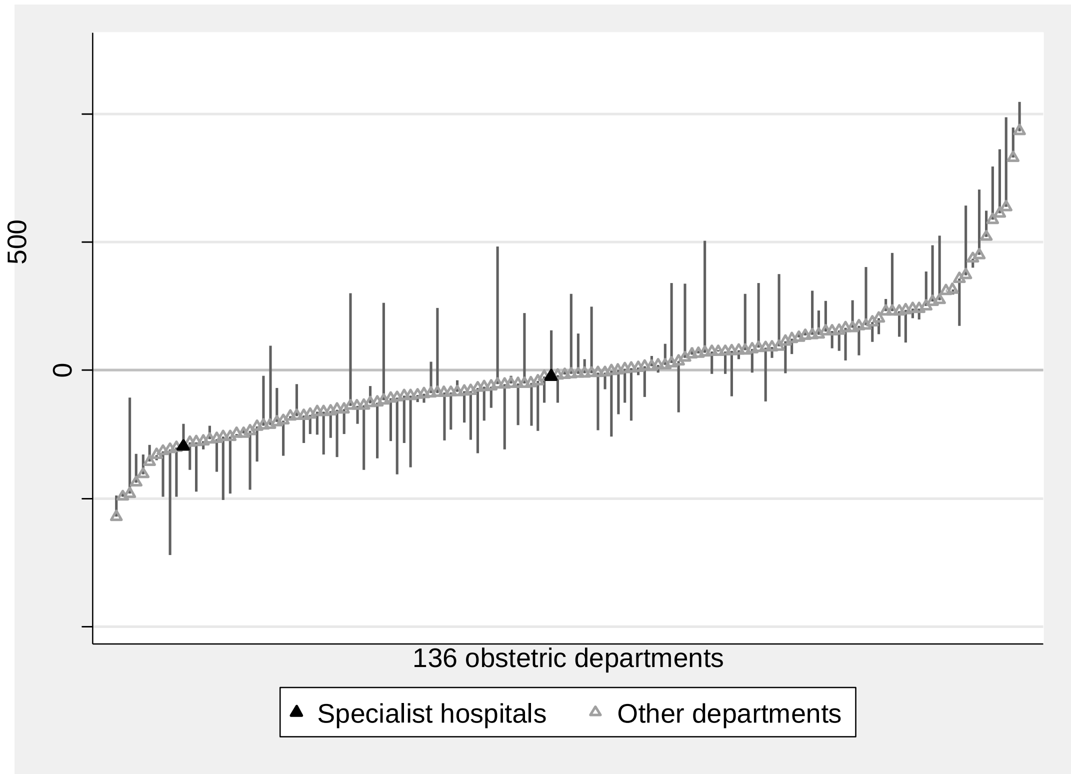
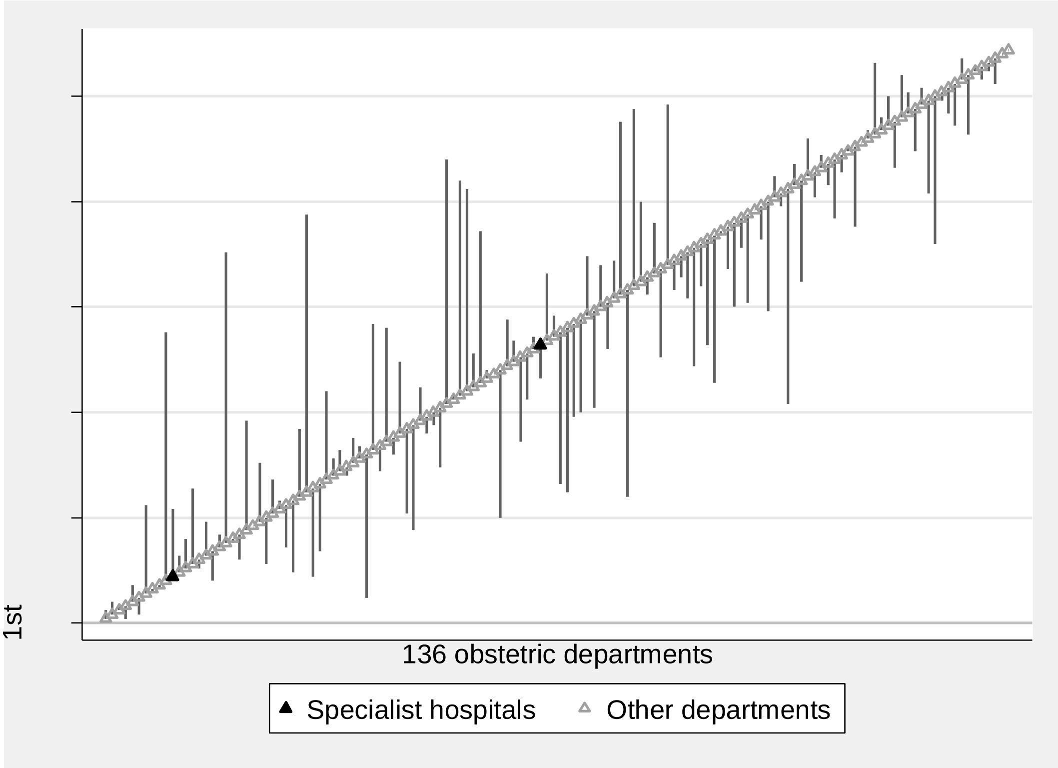


Figure 6 Departmental rank based on standardised average costs for all obstetrics patients compared to rank from analysis of maternity only.



Appendix 1: Starting and analytical samples

From a starting sample of 1,009,747 patients admitted to obstetrics departments during 2005/6, a number of records were dropped from the analysis for the following reasons.

- We omit eight hospitals where fewer than 1,000 patients are recorded in the obstetrics department.[vii] 1,125 patients are dropped because of this.
- Two hospitals did not use the obstetrics specialty code when making their cost returns, making it impossible to match their HES and cost data. Three other hospitals failed to report costs for a high proportion of the HRGs to which their patients were allocated. These five hospitals are excluded, meaning that 30,895 patients are dropped from the analysis.[viii]
- For 13,063 patients, there was no corresponding reference cost reported by the patient's hospital for the HRG to which they were allocated, meaning that a cost could not be assigned to them. These losses were not at random being concentrated among a selective set of hospitals.[ix]
- Patients assigned to "U" HRG codes are dropped, of which there were 12,014.
- A small number of obstetrics patients are recorded as having invalid or very long lengths of stay. Some of these values may be due to errors in recording either the date of admission or date of discharge, although some may be genuine values. Conservatively we have decided to drop 133 patients with a length of stay of more 100 days.
- Finally, we exclude 260 observations with a cost in excess of £15,000.

Table A1 Starting and analytical samples		
	observations	%
Starting sample	1,009,747	100.00%
Drop activity in low volume NHS hospitals	1,125	0.1%
Drop hospitals that did not assign obstetrics specialty code in their Reference Cost return or that had low volumes after matching	30,875	3.1%
Drop activity where that could not be matched to Reference Cost data	13,063	1.3%
Drop activity assigned to U code HRGs	12,014	1.2%
Drop FCEs with LoS more than 100 days	133	0.0%
Drop FCEs with cost more than £25,000	260	0.0%
Sample for analysis	951,277	94.3%

Appendix 2: Assigning reference costs to individual 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 obstetrics department, *j*, the following will be reported:

- Average cost per day case in HRG *h*: c_{hj}^{d}
- Average cost for elective patients in HRG *h* with a length of stay below HRG-specific trimpoint value: c_{hj}^{e}
- Excess *per diem* cost for an elective patient in HRG *h* who stays in hospital beyond the HRG-specific trimpoint: ex_{hj}^{e}

- 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_{hj}^{n}
- Excess *per diem* cost for a non-elective patient in HRG *h* who stays in hospital beyond the HRG-specific trimpoint ex_{hj}^{n}

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_h^e as the elective trimpoint in days and t_h^n as the nonelective trimpoint for HRG *h*.[x]

The costs provided by each hospital are assigned to each patient record in HES, according to the type of admission and how long each patient stays in hospital, as follows:

- If the patient was treated as a day case $if \quad a_{ihj}^{d} \rightarrow c_{hj}^{d}$
- If the patient was an elective with length of stay at or below the elective trimpoint $if\,(a_{ihj}^{e}, L_{ihj} \leq t_h^e) \rightarrow c_{hj}^{e}$
- If the patient was an elective with length of stay above the elective trimpoint $if\,(a_{ihj}^{e}, L_{ihj} > t_h^e) \rightarrow c_{hj}^{e} + \left[ex_{hj}^{e} \times (L_{ihj} - t_h^e)\right]$
- If the patient was non-elective with length of stay at or below the non-elective trimpoint $if\,(a_{ihj}^{n}, L_{ihj} \leq t_h) \rightarrow c_{hj}^{n}$
- If the patient was a non-elective with length of stay above the non-elective trimpoint $if\,(a_{ihj}^{e}, L_{ihj} > t_h^n) \rightarrow c_{hj}^{n} + \left[ex_{hj}^{n} \times (L_{ihj} - t_h^n)\right]$

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[i] In further analyses we also sub-divide patients on the basis of their length of stay, details being available here http://www.york.ac.uk/inst/che/pdf/rp49.pdf

[ii] Rather than dummy variables, it is common to construct a casemix index to capture cost variation across HRGs. Construction requires attaching a resource weight to each HRG to allow aggregation. In this study, the relatively small number of HRGs and large sample size allow us to avoid making assumptions about HRG relative weights and, instead, we estimate weights from the data.

[iii] http://www.ic.nhs.uk/webfiles/publications/esr_earnings_2007-7/July%202007%20Earnings%20Estimates%20Tables.pdf accessed 27/11/08

[iv] http://www.timesonline.co.uk/tol/life_and_style/health/article5168353.ece accessed 17/11/08; Fothergill, personal communication; http://www.nhsla.com/NR/rdonlyres/8A429D32-B5F2-41CE-A60F-087775DA28DC/0/NHSLAFactsheet5200506.xls accessed 11/11/08.

[v] Although there is evidence of heteroscedasticity in patient costs, transforming costs into logarithmic form is not required to our analysis. OLS provides consistent estimates of departmental fixed effects which are the main objective of our analysis in the first stage. Using log transformation may improve the estimation of the SE, but will result in estimated coefficients based on geometric rather than arithmetic mean. Retransforming such coefficients is not straightforward in the presence of heteroscedasticity (Manning 1987). We obtain consistent SE by applying the cluster robust estimator.

[vi] While the Breush-Pagan test for test for heteroshedasticity is negative in the second stage model (equation 2) this is known to be not completely reliable in small samples (Long and Ervin, 2005). Therefore, we apply Efron standard errors.

[vii] RC1 Bedford Hospital NHS Trust (18 FCEs), RD1 Royal United Hospital Bath NHS Trust (50), RDZ The Royal Bournemouth And Christchurch Hospitals NHS Foundation Trust (9), RG3 Bromley Hospitals NHS Trust (97), RLN City Hospitals Sunderland NHS Foundation Trust (547), RN7 Dartford And Gravesham NHS Trust (124), RNH Newham University Hospital NHS Trust (277), RXW Shrewsbury And Telford Hospital NHS Trust (3)

[viii] RG2 Queen Elizabeth Hospital NHS Trust (11,676 FCEs), RJ1 Guy's And St Thomas' NHS Foundation Trust (5,354), RAJ Southend University Hospital NHS Foundation Trust (10,590). RBZ Northern Devon Healthcare NHS Trust (1,297), RNJ Barts And The London NHS Trust (1,998).

[ix] Some departments have a minimal number of obstetrics patients assigned to a diverse range of HRGs. Examples are RGQ Ipswich Hospital NHS Trust (where 1,214 FCEs are allocated to 27 HRGs for which costs are not reported); RQM Chelsea And Westminster Hospital NHS Foundation Trust (849 FCEs, 63 HRGs).

[x] Trimpoints are revised periodically by the Information Centre. We have applied the trimpoints that were published alongside the national tariff for 2005/6 http://www.dh.gov.uk/en/Publicationsandstatistics/Publications/PublicationsPolicyAndGuidance/DH_4091529 accessed 15/9/08