Substituting inpatient for outpatient care: what is the impact on hospital costs and efficiency?

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Introduction

In the past most hospital patients were treated on inpatient wards. Treatments were demanding and hence it was necessary for patients to stay on the ward for days after a procedure. Attention started to be paid to the high cost of inpatient care in the 1970s (Davis, Russell 1972); the substitution of inpatient care to ambulatory care was seen as a means to reduce rising hospital costs. Substitution required medical and technological development and therefore it could not take place to a significant extent until the 1980s. A breakthrough for the expansion of ambulatory care was the development of minimally invasive surgery alongside short-acting anaesthesia; this made it possible to treat surgical patients without the requirement of an overnight stay in a hospital. Delivery of complex medical treatments such as dialysis and chemotherapy also became possible in the ambulatory setting. As a consequence of the development of daycare the average length of stay in a hospital started to fall significantly; in 1970 the average LoS in acute care hospitals in European Union countries was 16.5 days, whereas in 1996 it had nearly halved to 8.6 days (WHO 2001). By 2004 the average LoS in acute Finnish hospitals had fallen to 3.9 days (Niemi, Pelanteri 2005).

Alongside daycare, ambulatory care encompasses attendance in outpatient clinics and emergency departments. A common feature for all these activities is that a patient stays in a hospital for less than 24 hours. In this paper we define this group of ambulatory activities as 'outpatient care', thus covering daycare and outpatient visits. Inpatient care still remains an essential function of a hospital as there are patients for whom treatment in outpatient setting is not an alternative.

In Figure 1 a summary of treatment pathways for hospital patients is depicted. Patients can access hospital treatment either via a GP's referral to specialised care or via an emergency department. Whichever route is taken into the hospital setting, first a consultant makes a diagnosis and then decides either to discharge a patient from care at this point or to provide further treatment on an inpatient or outpatient basis. This choice between alternative settings is the point in treatment pathway we are interested in this paper (red colour in Figure 1). Outpatient care can be a substitute for inpatient care only to a limited extent, as the more complex the patient the less possible it is to treat him as an outpatient. The potential for substitution between settings, however, is not constant over time because the continuous development of outpatient procedures and supportive services increases the possibility to treat more complex cases in outpatient settings. As a consequence the average complexity of patients remaining in the inpatient settings should rise over time. At the same time the increased outpatient capacity makes it possible to treat an increasing amount of less complex patient cases, which are increasingly diagnosed because of improved diagnostic tests. As such, the advantages of outpatient care are that 1) it releases capacity in the inpatient setting to concentrate on more complex patient cases, and 2) it make it possible to treat more patients with existing resources.

In many countries there is increasing demand for hospital treatment and substitution towards outpatient care is seen as as a tool to increase patient throughput. Hospitals are not, however, in an equal position in adopting new technologies as they usually require expensive initial investments. For instance introducing day surgery requires considerable investment in terms of educating hospital staff in order to provide them with skills necessary for undertaking procedures and increasing operating theatre capacity. This might affect hospitals' short term possibilities to improve their productive efficiency in terms of being able to produce output with lower costs.

The effect of outpatient care on hospital efficiency is a fairly new research area as it has been directly studied only in Norway previously. The studies by Kittelsen and Magnussen (2003) and Martinussen and Midttun (2004) suggest that increased outpatient rate might have a positive effect on efficiency. Information on the overall effect of outpatient activities on both hospital costs and efficiency is not available and this is what we aim to address in this study. In this paper we report the results of panel data estimation using Finnish hospital data from 2003 to 2006. The main interest of the study is to find out whether the increased share of outpatient activities, in terms of the overall share of outpatient care or particularly the share of daycare, has affected the costs and cost efficiency of Finnish hospitals. The estimation of these effects is undertaken by using stochastic frontier analysis (SFA) following Battese and Coelli (1995).

The paper is organised as follows. First SFA technique and the Battese and Coelli (BC) model will be introduced in more detail, followed by a description of the data and variables used in the empirical analysis. After this the empirical model and estimation results will be introduced. In the last section discussion and conclusions will be given.

Stochastic frontier model for panel data

Stochastic frontier analysis in its early form was developed by Feldstein (1967). In that time the method used was Corrected OLS (COLS), which did not distinguish between error and inefficiency. In response to concerns that COLS may confuse random variations in productivity with variations in efficiency, SFA was developed further independently by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

SFA is a parametric technique which uses econometric tools to estimate a best-practice frontier. It is assumed in the model that all decision making units (DMUs) face the same production (or cost) function. The purpose is to decompose variations from the best-practice frontier into random (stochastic) error and deterministic error, which is assumed to represent inefficiency.

The use of panel data in stochastic frontier analysis was pioneered by Pitt and Lee (1981) and Schmidt and Sickles (1984). The study by Linna (1998) was one of the first studies in which stochastic frontier analysis was applied to hospital panel data. After it, similar type of studies have been undertaken for example with U.S (Rosko 2004), UK (Ferrari 2006), and German (Frohloff 2007) data.

When using panel data, the model takes the form:

$$Y_{it} = \alpha + \beta x_{it} + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the production at the t-th observation (t = 1,2,…,T) for the i-th DMU (i = 1,2,…,N); x_{it} is a $(1 \times k)$ vector of known functions of inputs and outputs of production and other explanatory variables associated with the i-th DMU at the t-th observation; β is a $(k \times 1)$ vector of unknown parameters to be estimated; and ε_{it} represents the error term, which consists of two components,

$$\varepsilon_{it} = v_{it} \pm u_{i(t)} \tag{2}$$

The v_{it}s are assumed to be iid $N(0,\sigma_v^2)$ random errors, as in the classic OLS model, independently distributed of the $u_{i(t)}s$ and time varying; the $u_{i(t)}s$ are non-negative random variables associated with inefficiency. In a simple form (time invariant model), the assumption is that inefficiency is constant over time. This assumption can be relaxed in which case inefficiency, u_{it}, is allowed to change over time (time varying model). The $u_{it}s$ are assumed to be independently and non-normally distributed with possible distributions being half-normal, exponential, gamma, and truncated-normal.

Because of the different distributions for the random component, v_{it}, and inefficiency component, u_{it}, the distribution of ε_{it} gives evidence whether there is inefficiency or not. If the distribution of

ε_{it} is normal all the residual variance is interpreted as arising from random noise, and in contrast, if ε_{it} is skewed this is taken as evidence that there is inefficiency in the sample.

Many empirical studies have analysed efficiency using a two-stage process in which a production (or cost) frontier is first estimated using SFA techniques and the efficiency estimates (u_{it}) are then regressed against a set of variables that are thought to explain difference in efficiency within the sample. This two-stage process is problematic because the second stage regression is built on the assumption that the dependent variable (u_{it}) is independently distributed. However, this is clearly false because the efficiency of each observation is estimated in relation to the rest of the sample. Failure to satisfy the assumption of independence leads to biased standard errors which invalidates significance tests.

To address this shortcoming Battese and Coelli (1995), have implemented a single stage procedure in which factors that explain levels of production (or cost) and factors that explain relative efficiency are considered simultaneously, using a model of the form:

$$Y_{it} = \alpha + \beta x_{it} + u_{it}\,(\delta\, z_{it} + W_{it}) + v_{it} \tag{3}$$

Here the $z_{it}s$, are used to explain the inefficiency effects, $u_{it}s$ with $u_{it} \sim N(z_{it}\delta,\, \sigma^2_u)$ being truncated at zero from below; z_{it} is an $(1 \times m)$ vector of explanatory variables associated with production inefficiency over time; δ is an $(m \times 1)$ vector of unknown coefficients; and W_{it} is a random variable with a skewed distribution.

There is no strict basis to guide the decision about what variables should appear in each part of the specification and the choice is likely to be context-specific. In our formulation, the x variables chosen to explain variation in the level of costs are those considered at least partially exogenous to managerial control. In the short term, at least, hospital management has to minimise cost subject to externally imposed constraints on wage level and given the existing capital stock. The z variables chosen to explain variations in efficiency are those thought to reflect the relative competence of management in acting within their constrained environment, such as their level of skill or effort, which are typically poorly observed. Here we select variables that describe the inpatient/outpatient mix of activities and the quality of coding of medical records as indicators of managerial competence.

Maximum likelihood is used for simultaneous estimation of the stochastic frontier and inefficiency models. The estimation can be undertaken with Limdep 9.0 (Hilbe 2006) software. To test the significance of inefficiency term, Limdep produces an estimate for λ which tells if the ratio of σ_u over σ_v is significant. It also tests the significance of σ_u directly.

Data and variables

The data are a sample of 33 public acute care hospitals in Finland in years 2003−2006. The main data source is the Finnish Hospital Benchmarking dataset which includes patient level information on all the services produced in Finnish public hospitals and also the costs of services[1]. We select six specialties in order to concentrate the analysis into specialties which produce the most outpatient services. These specialties are internal medicine (specialty number 10), surgery (20), obstetrics and gynaecology (30), paediatrics (40), cancer treatments (65) and lung treatments (80). In small hospitals some of these specialties are very small, or nonexistent, and therefore we include only those specialties with a total operating cost of more than €1.5m. Two local hospitals are excluded completely because they do not have all the required information for each of the years of interest. This makes a balanced panel data set of 584 observations.

A list of variables used in the analysis is given in Table 1 and descriptive statistics for each of the years of interest in Table 2. In most SFA models the explanatory variable has been measured as total costs (Hollingsworth 2003, Vitikainen 2006). In this paper we estimate a cost function in which net operating costs is the dependent variable. Net operating costs include all production-related (direct and indirect) costs of a hospital unit and depreciated capital costs but exclude additional personal revenues and purchasing costs for special services (not included in outputs). In Finland specialties operate as independent units with their own cost accounting. As such, the allocation of costs due to patient care to each individual specialty is considered reasonably accurate. There are, however, some costs (e.g. administrative costs) that can not be allocated to specialties perfectly and this may cause some inaccuracy in the measurement of specialty level costs. In the Benchmarking project hospitals use the same rules in documenting capital costs.

Three variables identify input prices, i.e. $w = 1,\ldots,3$ where w_1 = average monthly salary for physicians, w_2 = average monthly salary for nurses, and w_3 = average monthly salary for other

[1] More information on the Benchmarking project and data collection can be found from http://info.stakes.fi/benchmarking/EN/benchmarking.htm

staff. In Finland wage levels are mostly determined in negotiations between unions and employers and therefore there is little variation between hospitals and wage levels are considered exogenous to managerial control. However within broad wage categories the mix of different types of physicians, nurses and other staff is subject to variation, and is greatest among physicians. In a situation where there is a lack of qualified physicians in the country some hospitals are forced to hire 'more expensive' physicians than others. The salary scale for physicians is wide and employment at different points of the scale causes a lot of variation to the overall cost of physicians between hospitals. The salary scale for nurses is more contained and the structure of nursing labour force in hospitals is more fixed than physicians, and this creates less variation in the mean salary of nurses. The group of other staff includes different types of therapists (e.g. physiotherapist), social workers, secretaries etc. and, as such, is fairly heterogeneous with respect to salaries. The amount of these employees in a hospital, however, does not vary greatly and therefore the average salary costs are similar between hospitals. We take the mixture of different types of employees into account by weighting monthly salaries by the volume of different types of employees. We assume that there is no variation in wages across specialties. The average salaries are defined based on data from Statistics Finland[2].

Capital stock is measured as the number of hospital beds. Information on the exact number of beds has not been available in Finnish hospitals in recent years and therefore we calculate the capital variable as the total number of bed-days divided by 365. Because of the queues for hospital treatment, all the beds can be assumed to be occupied at all times and therefore this calculation gives a fairly good approximation of the size of hospital inpatient units.

Three variables identify outputs, i.e. $y = 1,\ldots,3$ where y_1 = weighted number of inpatient admissions, y_2 = weighted number of day cases (including day surgical cases), and y_3= weighted number of outpatient visits. The weighting is undertaken by DRG cost weights. In Finland NordDRGs are used. The principle of NordDRG Full grouper (FullDRG), which we use here, is described in detail in Vitikainen et al. (2008). We use the 2005 version of the FullDRGs in grouping the data for each year in order to make all the years comparable and we employ a standard set of cost weights across all years.

[2] Information on wages can be found from the website of Statistics Finland: http://www.tilastokeskus.fi/index_en.html

In the Benchmarking database treatment time is defined by using arrival and discharge dates, but the exact arrival and discharge times are not provided. This makes the definition of day cases in medical specialties problematic. A patient is considered as a day case when he comes in to the ward in the morning and leaves during the same day. In this case the arrival and discharge dates are the same. This is not, however, good enough definition for a day case because the arrival and discharge dates are the same also for some other patients, e.g. for patients who come in to the ward as emergency at night but do not need to stay on the ward longer than one day (dashed line in Figure 1). Considering this, we define a day case as having the same arrival and discharge dates, and a reason for an admission being other than emergency.

Hospital outpatient care consists of daycare admissions, scheduled visits and emergency visits. The overall share of outpatient activity of the unit's total production defines the concentration on outpatient care in each hospital unit. In 2006 outpatient care covered approximately 35 per cent of hospitals' total production (Table 2). Daycare, especially day surgical care, is the part of outpatient care that has been of most policy interest and therefore we pay a special attention to it. The share of daycare of total inpatient care tells how much hospital units concentrate on treating patients as day surgical cases in surgical specialties and as day cases in medical specialties instead of inpatient cases. This share has been around 16 per cent in recent years (Table 2).

The FullDRG grouper separates day cases by allocating them into special O-groups. The O-groups are equivalent to inpatient groups except that they, in general, have lower cost weights compared to inpatient groups. Differentiated weights give an accurate approximation of total costs of production as usually daycare admissions cost less than inpatient admissions – as such, in the cost function it is appropriate to use separate weights. However, when calculating the DRG weighted sum of outputs the shift of service production from inpatient setting to daycare setting appears as a reduction in overall output. This may have an adverse effect on measured efficiency if the reduction in costs due to outpatient care is not enough to compensate the reduction in the weighted output. The same effect applies to the shift from inpatient care to outpatient visits. The "pure" outpatient groups have even lower cost weights than the daycare O-groups. Considering this, in efficiency measurement it would be sensible to use common weights to patient cases with the same diagnosis and procedure code irrespective of whether they are treated in inpatient or outpatient setting. In Finland DRGs are used as a billing instrument between hospitals (providers) and municipalities (purchasers), but not as a hospital payment system. For this purpose the differentiated weights have been appropriate and hence it has not been necessary to create common weighting system. It has not yet been shown if this kind of weighting causes a bias in time series efficiency measurement and hence it is the question we try to answer in this study.

We select a set of control variables in order to eliminate the effect of diagnosis and procedure code documentation quality, and clinical quality factors on hospital costs and efficiency. The quick discharge of patients after an operation might cause the rate of readmissions to grow which, in turn, might have an effect on hospital costs. Here we measure readmissions as the ratio of the number of readmissions to the counts of inpatient and daycare admissions. The average rate of readmissions has remained fairly constant over time being approximately nine per cent (Table 2). The DRG output grouping system relies on the accurate documentation of diagnoses and procedure codes. DRGs have not yet been systematically used in outpatient care and therefore little attention has been paid to documentation quality until recently. In particular, coding of procedures is poor. In 2003 only seven per cent of procedure codes were documented accurately. Since then coding has improved, but even in 2006 it was at unsatisfactory level, i.e. 17 per cent (Table 2). The documentation rate for primary diagnoses has been better than that for procedure codes, i.e. on average 85 per cent in years 2003–2006.

The empirical cost function model

A hospital can be presented as a production unit which transforms labour and capital inputs into inpatient and outpatient services, with input prices and output levels used to explain the total operating cost of a hospital unit. These variables are included in the stochastic frontier cost function. We also include (time invariant) teaching and specialty dummies to capture hospital or unit specific aspects of provision that are not adequately accounted for by the measure of output. We follow the seminal paper of Farrell (1957) by defining efficient units as those producing a given level of output at lowest costs. The inefficiency of all other units is defined as the ratio of their actual to potential production, i.e. as a distance from the cost frontier.

The estimated coefficients of the cost function is one of the aspects we are interested in this study. In addition, the aim is to find out how different factors affect the estimated cost inefficiency. In order to achieve both of these results we use the panel data stochastic frontier model following Battese and Coelli (1995) which estimates the cost function and regression for the explanation of inefficiency term simultaneously. The model allows efficiency to vary over time. We assume that inefficiency within the sample is half-normally distributed[3].

We start our estimation with a traditional ordinary least squares (OLS) estimation in order to test the reliability of parameter estimates produced by the BC model. The cost function takes a log-linear Cobb-Douglas form

$$\ln \frac{C_{it}}{w3} = \beta_0 + \beta_{1m} \ln(y_{mit}) + \beta_{2k} \sum_{k=1}^{3} \ln \frac{w_{kit}}{w3} + \beta_3 \ln READM_{it} + \beta_4 Dteach_i + \beta_{5s} \sum_{s=1}^{5} Dspec_i + \varepsilon_{it} \qquad (4)$$

where C denotes the operating cost of unit i at time t, y the vector of outputs and w the vector of input prices. In order to fulfil the required property of linear homogeneity in input prices we normalise the operating cost and input price variables with respect to the average monthly salary for other staff following Greene (2005). The capital (BEDS) variable had to be excluded from the cost function because of its high correlation with the output variables.

In the OLS model coefficients for the output variables tell the relative impact of the level of inpatient care, daycare and pure outpatient care on operating costs and can be interpreted as elasticities. The cost of inpatient admissions is high relative to daycare admissions and outpatient visits and hence we expect the coefficient for inpatient output to be higher than that for daycare and outpatient output. We expect all the cost elasticities to be positive, i.e. an increase in output and input levels increase costs. The READM variable is seen as a clinical quality indicator; the poorer the quality of treatment is the more readmissions patients have and the higher the operating cost is likely to be.

Teaching dummy is included into the model in order to account for hospitals which have a lot of teaching activities, i.e. to university hospitals. These hospitals have been found to have higher costs compared to non-teaching hospitals (Linna, Häkkinen 1998) and also the complexity of their caseload is underestimated by the DRG grouping system (Sutherland, Borz 2006). Specialty dummies capture the effects of individual specialties on operating cost. It is assumed that specialties are clustered, i.e. the same specialties have a similar cost structure. Specialties with a lot of surgical patient cases (surgical, and obstetrics and gynaecology specialties) are expected to

[3] Changing the assumption for error distribution has only a marginal effect on estimation results.

have higher costs than those with a large share of medical patients (internal medicine, pediatrics and lung treatments specialties). This is because surgical procedures tend to be more expensive than medical interventions. Similarly, the cancer treatments specialty is expected to have high costs particularly because the drugs used in chemotherapy treatment are very expensive.

The frontier part of the BC model is equivalent to the OLS model except that the error term is divided into two parts as described in the previous section of this paper. As such, the cost frontier takes the form

$$\ln \frac{C_{it}}{w3} = \beta_0 + \beta_{1m} \ln(y_{mit}) + \beta_{2k} \sum_{k=1}^{3} \ln \frac{w_{kit}}{w3} + \beta_3 \ln READM_{it} + \beta_4 Dteach_i + \beta_{5s} \sum_{s=1}^{5} Dspec_i + v_{it} + u_{it} \quad (5)$$

The inefficiency effects are assumed to be defined by

$$U_{it} = \delta_1 (OUT\%_{it}) + \delta_2 (DCARE\%_{it}) + \delta_3 (OUTPDG\%_{it}) + \delta_4 (OUTPROC\%_{it}) + W_{it} \quad (6)$$

A recommendation is that the factors used as explanators of relative efficiency are under the control of hospital administrators (Smith 1995). We argue that the the rates of overall outpatient and daycare activities, as well as the quality of diagnostic and procedure coding in outpatient care are of this nature. We would expect that higher values of each of these factors to have a positive impact on efficiency. However, because the DRG system assigns lower weights to outpatient and daycase activity relative to inpatient activity, the relationship with efficiency may appear negative. If this measurement bias exists common weighting for inpatients and outpatients should be created.

The improved quality of diagnosis and procedure code documentation in outpatient care is expected to have a positive effect on efficiency. As a consequence of poor documentation a large share of hospital outputs is categorised into the DRG group 999 which refers to "short treatment without a diagnosis"[4]. A cost weight for this group is low (= 0.283) compared to most of the outpatient groups in the FullDRG grouper. As such, the DRG weighted output is lower compared to a situation where most of the outputs would be able to be allocated to the 'correct' DRG groups based on diagnoses and procedure codes.

[4] The 2005 FullDRG groups and equivalent cost weights can be found from the website of the Finnish Consulting Group; http://norddrg.kuntaliitto.fi/4NordDrg%20Suomi/2painot/DRGpain.htm.

Results

The estimations using the Cobb-Douglas models are presented in Table 3. The Hausman test for the OLS model suggests that endogeneity is not a problem (H=20.8), and the R-squared and F-test statistics support the goodness of the model. Signs for the estimated coefficients for the BC model are similar to the OLS model and also the magnitude of coefficients are approximately the same. This gives evidence that the maximum likelihood estimates are similar to OLS estimates.

All the cost elasticities are, as expected, positive and for most of the variables highly significant. Both OLS and BC models suggest that inpatient care increases operating cost at greater rate than outpatient care; a ten per cent increase in inpatient output increases costs by approximately six per cent and the equivalent increase in outpatient output increases costs by approximately four per cent. Outpatient visits have a greater influence on costs than daycare simply because a larger volume of outpatient care is provided in a pure outpatient setting, comprising on average 31 per cent of hospitals' total production. The equivalent figure for daycare is only four per cent. There is no significant relationship between the readmission rate and costs probably because there is not enough variation in the readmission rate. The results reveal that in the pediatric and lung treatments specialties the operating cost is significantly lower and in the cancer treatment specialty higher compared to the internal medicine specialty.

In addition to the variables reported in Table 3, we experimented with other variables in the cost function but for different reasons they had to be excluded. The reasons for exclusion and their impacts on other coefficients are summarised in Table 4. The insignificant coefficients for year dummies suggest that there was no significant change in operating cost over time, i.e. the cost frontier did not change its location over the period analysed. Patients with atypically high or low costs are often excluded from DRGs and taken into account separately. We considered this by including an outlier variable into the cost function, but because of its high correlation with the inpatient variable it had to be excluded from further estimation. The inclusion of hospital dummies into the model yielded a collinearity problem.

In the BC model λ and the variance of *u* are both significant indicating that there is inefficiency in the sample. The share of *u* explaining the overall error variance ($\gamma = \sigma_u^2 / \sigma_v^2 + \sigma_u^2$) is 68.3 per cent. The coefficient for OUT% variable is significant and positive suggesting that an increase in the share of outpatient care is associated with lower efficiency, while the proportion of daycare is not significant. This counterintuitive finding is probably due to the low weight given to these activities by the FullDRG system. The results also suggest that the quality of primary diagnoses documentation in outpatient care affects the estimated cost efficiency while there is no significant association with coding of procedures.

We also explored variables measuring inhospital mortality (IHM%), specialization degree (the share of the largest Master Diagnosis Category (MDC) in terms of costs of overall production) (SD%), the share of patients allocated to DRGs with complications (COMPL%) and the year dummies. When all of these were included into the model Limdep 9.0 software was not able to run the model. Without the year dummies the estimation was successful, but produced insignificant coefficients across all variables. The insignificant coefficients suggest that hospital units do not benefit from specialisation in terms of efficiency and that so called DRG creep is not a problem in Finnish hospitals. DRGs with complications have higher cost weights compared to the equivalent groups without complications and, as such, hospitals might try to improve their efficiency by 'upgrading' their patient to DRGs with higher cost weights. The exclusion of these variables did not affect the coefficients of other variables markedly. The main reason for the exclusion of inhospital mortality variable was its inability to measure hospital treatment related mortality properly; of patients who die following hospitalisation most do so after being discharged. Post-discharge mortality is not available in Finnish registers and therefore we were not able to include a variable measuring the overall hospital treatment related mortality in our analysis. After the exclusion of all the variables mentioned above we included the year dummies into the model, but again they had highly insignificant coefficients suggesting that hospital efficiency did not change over time.

Discussion and conclusions

A recent trend in hospital sector has been to shift service production from inpatient setting to outpatient setting. This has shortened hospital length of stay for patients and made it possible for hospitals to treat more patients. Whether this trend has had an impact on hospital costs and cost efficiency is the question we have tried to address in this study. The stochastic frontier procedure developed by Battese and Coelli (1995) has been used in the analysis in order to be able to estimate the impact of increased outpatient care on both costs and cost efficiency.

Our results reveal that outpatient services, including daycare and outpatient visits, have a cost reducing effect. At the same time, however, the results suggest that outpatient activity appear to have an adverse effect on cost efficiency. This is an opposite finding to the previous Norwegian studies by Kittelsen and Magnussen (2003) and Martinussen and Midttun (2004). In these studies outpatient output has been measured as hospital's revenue related to outpatient care because at the time the studies have been undertaken outpatient DRGs have not been available. In our study DRG weighting for original outputs has been used. The different way of measuring outpatient outputs probably explains our differing result. The FullDRG output grouping has features that strongly affect efficiency measurement. When weighting outputs with DRG cost weights outpatient activities get a significantly lower weight compared to inpatient activities because, in general, they cost less. This kind of principle works well in cost analysis and even when using DRGs as a billing instrument, but in efficiency measurement it causes a bias. In efficiency measurement inpatient and outpatient cases with the same diagnosis and procedure should be weighted equally irrespective of the place of treatment. Common weights for inpatient and day cases are easily found because of the equivalent inpatient and daycare DRG groups, but it does not completely solve the problem as daycare comprises only a small share of total outpatient care. In pure outpatient setting the poor documentation of diagnoses and procedure codes makes it difficult to find the equivalent outpatient cases to inpatient cases. As such, creating a common weighting will be a challenge.

The Battese and Coelli model used in this paper is fairly complex and hence requires an accurate specification of the model. While trying different specifications we found that the inefficiency part of the model in particular was very sensitive to the decision of which variables were included. The results of the models reported in this paper are, in general, in line with the hypotheses based on production theory and previous findings. This provides evidence that we managed to find a model specification that fits the data fairly well and this increases the reliability of our results.

Hospital outpatient care is a relatively new research area and therefore much information on its effects does not exist. Hospitals, as well as the health care sector as a whole, face great pressure to control continuously growing costs and from this point of view our results are encouraging for hospital administrators. Concentration on outpatient setting is worthwhile from the cost point of view. To find out an unbiased effect of increased outpatient care on hospital efficiency requires more work. In future research it is necessary to go down to the individual DRG level in order to find a solution to the measurement bias inherent in the DRG system against outpatient relative to inpatient activities. That means that it is impossible to account accurately for the impact on efficiency of true instances of substitution between settings. Until we are able to compare substitution of treatments across settings on a like-for-like basis, reliable conclusions concerning changes in efficiency resulting from changes in care settings cannot be drawn.

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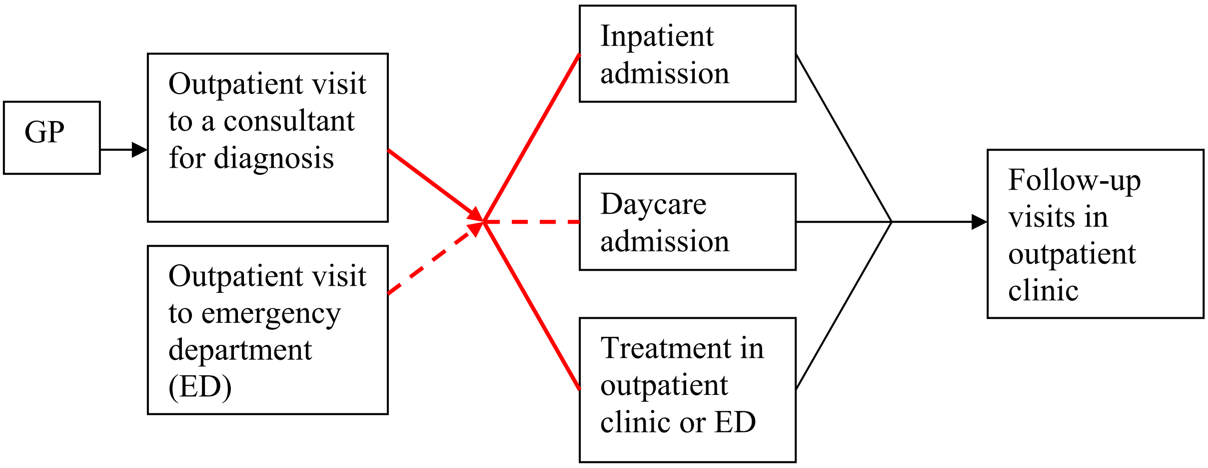

Figure 1 Treatment pathways for hospital patients.

Table 1 Variable definitions

	Variable name	Definition
Cost variable:	COSTS	Net operating costs including capital cost
Input prices:	W1	Average monthly salary for physicians
	W2	Average monthly salary for nurses
	W3	Average monthly salary for other staff
Capital variable:	BEDS	The estimated number of beds, calculated as the total number of bed-days divided by 365
Output variables		
Inpatient treatment:	ADM	Total number of DRG weighted admissions
Outpatient treatment:	DCARE	Total number of DRG weighted day cases
	OUTVIS	Total number of DRG weighted outpatient visits
Outpatient variables:	OUT%	The share of outpatient output of total production
	DCARE%	The share of day cases of the total inpatient care
Control variables:	READM	Ratio of the number of readmissions to the counts of inpatient and daycare admissions
	OUTPDG%	The share of outpatient visits with a primary diagnosis documented
	OUTPROC%	The share of outpatient visits with a procedure code documented
	Dteach	Dummy for teaching hospitals
	Dspec	Dummies for specialties

Table 2 Descriptive statistics

	2003		2004		2005		2006	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
COSTS (1000€)	16,856	27,739	17,439	28,004	18,156	29,774	18,483	30,052
W1	5,833	547	5,668	503	5,932	522	5,938	492
W2	2,285	96	2,246	131	2,332	125	2,312	107
W3	1,867	92	1,866	81	1,887	81	1,860	74
BEDS	53	68	53	69	53	69	53	76
ADM	18,788	29,346	19,366	30,403	19,923	31,860	19,871	30,643
DCARE	991	1,908	1,057	1,981	1,036	1,606	1,193	2,422
OUTVIS	7,573	10,312	7,930	10,686	8,254	11,141	8,343	11,252
OUT%	34.2	11.3	34.9	11.4	35.4	11.6	35.4	11.8
DCARE%	15.4	11.1	16.0	12.2	16.3	12.5	16.2	12.5
READM	9.0	3.3	9.0	3.4	9.0	3.6	8.8	3.6
OUTPDG%	81.2	19.1	83.3	18.8	86.5	18.1	87.9	17.9
OUTPROC%	7.2	14.3	10.7	16.6	16.2	20.3	16.6	21.6

Table 3 Parameter estimates for the OLS and BC cost function models.

	OLS coeff (t-value)	BC-model coeff (t-value)
Constant	-0.707*)	-0.877*)
	(-6.53)	(-8.12)
LNADM	0.574*)	0.603*)
	(24.31)	(22.12)
LNDCARE	0.037*)	0.043*)
	(5.44)	(5.54)
LNOUTVIS	0.359*)	0.338*)
	(14.39)	(13.31)
LNW1	0.431*)	0.434*)
	(5.41)	(5.78)
LNW2	0.015	0.091
	(0.09)	(0.51)
Dteach	0.167*)	0.146*)
	(5.8)	(3.6)
LNREADM	0.001	-0.007
	(0.06)	(-0.28)
SPEC20	-0.018	-0.039
	(-0.58)	(-1.03)
SPEC30	-0.027	-0.021
	(-0.95)	(-0.58)
SPEC40	-0.261*)	-0.282*)
	(-9.23)	(-9.9)
SPEC65	0.116*)	0.148*)
	(2.58)	(3.24)
SPEC80	-0.089*)	-0.076*)
	(-3.26)	(-2.82)
R-squared	0.977	
F-test	202.69	
P-value	(0.000)	
λ		1.448*)
		(10.98)
σ(u)		0.179*)
		(75.17)
OUT%		0.008*)
		(3.66)
DCARE%		0.001
		(0.21)
OUTPDG%		-0.004**)
		(-1.82)
OUTPROC%		-0.001
		(-0.43)

*) Significant at less than 5% significance level.
**) Significant at less than 10% significance level.

Table 4 Excluded variables

Variable	Reason for exclusion	Effect on other coefficients
Dt	Insignificant coefficients	No significant effect
OUTLIER	High correlation with the ADM variable	Diminished the estimated SE for the ADM variable
BEDS	High correlation with the ADM and OUTPAT variables	Diminished the estimated SEs for the ADM and OUTPAT variables, made the inefficiency model to work better
Dhosp	Collinearity problem	
IHM%	Insignificant coefficient	No significant effect
SD%	Insignificant coefficient	No significant effect
COMPL%	Insignificant coefficient	No significant effect