The impact of health care financing reform on the productivity change in Finnish hospitals

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Abstract

The purpose of this study was to analyse the development of productivity and efficiency in the production of hospital care in Finland during the period 1988-1994. A special interest was directed to the impact of health care financing reform in 1993. The analysis is based on the Malmquist index approach using linear programming. Positive productivity changes were found particularly towards the end of the observation period, although a few years did not show significant improvements in productivity and efficiency.

There was a significantly higher rate of productivity 1992 - 1993 and 1993 - 1994, suggesting that the state subsidy reform in 1993 may have strengthened hospitals' efforts to improve performance. The use of output based reimbursement was not markedly associated with increased efficiency or productivity.

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Key words: Hospital financing, Hospitals, Productivity, Malmquist indices

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INTRODUCTION

Most western countries have experienced a steady growth of health care expenditure over the past few years. In Finland, where hospitals account for 55 per cent of total health care expenditure, the government’s budget deficit has imposed unrelenting pressure on hospitals to contain costs. The usual explanations for increasing costs have been lack of incentives in the hospital reimbursement system, the adoption of costly new medical technologies and an ageing population along with the possibility of treating sicker patients. However, there has been surprisingly little study of the efficiency changes made in the organisation of health care delivery. Rising costs may be due to increasing inefficiency rather than technological improvements.

One controversial issue in health politics has been the role of government in the regulation of health care delivery. Moves towards deregulation or managed markets are commonly justified by efficiency (and hence, productivity) gains. The Finnish state subsidy reform of 1993 was expected to enhance productive efficiency by introducing competitive elements into health care. The reform allowed the municipalities to adopt a more active role as purchasers of hospital services as they became the budget holders of public health care money. This change in the financing system involved the introduction of performance based reimbursement and it encouraged municipalities to selective contracting.

The pressure to adopt new and costly medical technology has been particularly acute in the realm of specialized care provided by hospitals. However, although technological change should generally have a positive impact on productivity (a positive change in the production possibilities frontier), there is little empirical evidence of this. The adoption and diffusion of new technologies requires substantial efforts from hospitals, including the provision of education for medical and nursing students and the testing of new technologies by clinical research. Worldwide, the overall impact of teaching and research on hospital costs has been estimated to vary between nil and 25 per cent (Linna et al., 1998), though for teaching hospitals most estimates lie between 7 and 15 percent. The actual reimbursement of teaching and research in different countries varies from 8 to 22 per cent of hospitals' recurrent costs.

There has been only few attempts to evaluate the development of hospital productivity in Finland, usually involving unacceptable measures for produced output (Alander et al., 1990). Hospital productivity studies elsewhere have hardly succeeded any better, clearly due to incomplete statistics: bed-days or the number of admissions (without case-mix standardisation these are inadequate measures of hospital output) have been used in the majority of productivity studies. Teaching and research output is usually ignored and there are only a few examples where plausible methods for case-mix standardisation have been used (Magnussen, 1996; Burgess and Wilson, 1996). There is clearly a need for more realistic productivity estimates based on theoretically more satisfactory output measures.

In this study it was possible to observe the effect of technological change by measuring the shift in the production possibilities frontier. Nonparametric methods were used to calculate Malmquist indices of productivity change. The major patient output - inpatient admissions - was derived from discharge data from all inpatients on the basis of case-mix complexity (Diagnostic Related Groups, DRGs). In addition, teaching and research output was measured more accurately than in previous productivity studies.

BACKGROUND

Productivity is commonly defined as an index of outputs divided by an index of inputs. The methods for measuring productivity differ in how the weights for these indexes are determined. In the case of hospitals producing multiple outputs, factor prices are not typically available or do not reflect the marginal costs. Furthermore, if the issue of technological change is to be addressed, the measurement technique should be capable of separating the effects of efficiency change and frontier change in a panel data setting.

There are several alternative methods for handling these restrictions and making it possible to decompose productivity change into its sources - efficiency change and technological change. Deterministic frontier analysis (DFA), stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are all efficiency measurement techniques capable of using panel data. However, DFA distance functions are parametric and deterministic, confounding the effects of omitted variables and measurement errors, as well as possible misspecification of the functional form. According to Lovell (1996), the primary drawback with SFA is that not only the structure of technology is parametrized but also the structure of inefficiency. Kumbhakar (1990), and Battese and Coelli (1992), proposed a model where individual efficiency was allowed to develop according to exponential function. In this model every producer has the same pattern of efficiency change, which decreases, remains constant or increases with time. Later, Battese and Coelli (1995) proposed a model where inefficiencies are assumed to depend on a set of exogenous variables.

These SFA models share a common feature: without heavy parametrization, every producer is assumed to have the same time-pattern of efficiency change. Moreover, SFA models usually also require a neutral technical change common to all producers. Although there are many creative solutions to these problems, the flexible parametrizations consume degrees of freedom and create collinearity problems.

DEA models embody several alternatives for the treatment of efficiency and technical change. Tulkens and van den Eeckaut (1995) defined three kinds of frontiers for technology: i) contemporaneous, ii) sequential and iii) intertemporal. The sequential model uses an assumption of non-regressive technical change where any input-output combination feasible in the earlier periods is also feasible in all subsequent periods. The intertemporal model merges the data for all years into one set and calculates efficiency scores for the entire data set. The boundary shift of a reference set depends on the analyst's decision on the relevant observations to be included in the 'time window' within the panel. For example, using full data to construct a single intertemporal production set an assumption of no technological change is made. However, with the construction of a sequential production set some form of dependence is postulated between these sets. In another example, the non-parametric applications for Malmquist indices (Färe et al., 1989) use two adjacent cross-sections in time t-1 and t to calculate a geometric mean of the technologies as the reference technology. It is possible that these alternatives for measuring progress or regress by frontier shifts give conflicting results, since the choice of the reference frontier is different each time (Grifell-Tatje and Lovell, 1996).

However, the DEA model has a number virtues which have enhanced its popularity among productivity analysts. DEA is a non-parametric local index, which means that productivity change and its components are allowed to be producer-specific as well as time-varying, and there are no restrictions on the temporal patterns. Furthermore, using DEA it is not necessary to impose any behavioural assumptions such as cost minimisation, which is an important advantage in the analysis of public hospitals. Although the literature typically refers to DEA methods as being deterministic, it is possible to incorporate sensitivity analysis through bootstrapping (Simar and Wilson, 1998).

In this study DEA models were used to calculate Malmquist indices of hospital productivity. Primal production data were used to estimate distance functions. Finally, confidence intervals for the average productivity, efficiency and technology change indices were constructed by bootstrapping the geometric means using the technique suggested by Atkinson and Wilson (1995)

A MODEL OF PRODUCTION

Malmquist index for measuring productivity

Nonparametric frontier methods measure the efficiency of the decision-making unit (DMU) with a distance measure introduced by Shephard (1953) and first made operational by Farrell (1957). The efficiency of a unit is characterized by the distance between the unit's observed level of inputs and outputs and the best practice production frontier.

To account for temporal changes, the input-output vector (x^t, y^t) needs to be related at time period t to the technology $P^{t+1}(x^{t+1}, y^{t+1})$ at the following period. Then, input oriented distance functions can be defined as

$$D_I^t(x^t, y^t) = \max\left\{q : (x^t / q, y^t) \in P^t(x^t, y^t)\right\} \quad (1)$$

and

$$D_I^{t+1}(x^t, y^t) = \max\left\{q : (x^t / q, y^t) \in P^{t+1}(x^{t+1}, y^{t+1})\right\} \quad (2)$$

where the production technology at t is described by the set

$$P(x^t, y^t) = \left\{(x^t, y^t) : x^t \text{ can produce } y^t\right\} \quad (3)$$

Following Färe et al. (1989), using a piecewise linear reference technology with constant returns to scale (CRS) the input oriented distance function can be estimated as the solution to LP problem:

$$D^t_{I|CRS}(x^t, y^t)^{-1} = \min_z\{q: z \cdot Y \geq y_0,\ z \cdot X \leq q \cdot x,\ z_i \geq 0,\} \quad (4)$$

where z is a $n \times k$ vector of intensity variables. Caves et al. (1982) demonstrated how distance functions can be used to analyse productivity change. Färe et al. (1994) formulated the estimation of Malmquist indices with non-parametric LP models. According to Färe et al. (1994) the input-oriented Malmquist productivity index is

$$M_I^{t,t+1}(y^t, x^t, y^{t+1}, x^{t+1}) = \left[\frac{D_I^t(y^{t+1}, x^{t+1}) \cdot D_I^{t+1}(y^{t+1}, x^{t+1})}{D_I^t(y^t, x^t) \cdot D_I^{t+1}(y^t, x^t)} \right]^{\frac{1}{2}} \tag{5}$$

which is a geometric mean of the indices proposed by Caves et al. (1982). Färe et al. (1994b) decomposed (5) further into components of efficiency change (EC) and the change in production technology (TC) by

$$M_I^{t,t+1}(y^t, x^t, y^{t+1}, x^{t+1}) = EC_I^{t,t+1} \cdot TC_I^{t,t+1} = \left[\frac{D_I^t(y^{t+1}, x^{t+1})}{D_I^t(y^t, x^t)} \right] \cdot \left[\frac{D_I^t(y^t, x^t) \cdot D_I^t(y^{t+1}, x^{t+1})}{D_I^{t+1}(y^t, x^t) \cdot D_I^{t+1}(y^{t+1}, x^{t+1})} \right]^{\frac{1}{2}} \tag{6}$$

The cross-terms $D_I^t(y^{t+1}, x^{t+1})$ are solved similarly to (4) as

$$D_{I|CRS}^t(x^{t+1}, y^{t+1})^{-1} = \min_z \{q\colon z \cdot Y^t \geq y^{t+1},\ z \cdot X^t \leq q \cdot x^{t+1},\ z_i \geq 0,\} \tag{7}$$

and solving $D_I^{t+1}(y^t, x^t)$ needs only the switch of time superscripts in (7).

Some studies have decomposed Malmquist indices to take into account the effects of changes in scale efficiency (see e.g. Tambour, 1997) according to the model proposed by Färe et al. (1994a) using input distance functions with variable returns to scale (VRS) constraints (intensity variable summing up to one):

$$D_{I|VRS}^t(x^t, y^t)^{-1} = \min_z \{q\colon z \cdot Y \geq y_0,\ z \cdot X \leq q \cdot x,\ z_i \geq 0, \sum_i z_i = 1\}\ , \tag{8}$$

However, the use of variable returns to scale in the calculation of distance functions have been subject to some controversy (Ray and Desli, 1997). As demonstrated by Försund (1997), it is important to use CRS technology in the decomposition of (6) Färe et al. (1994b) used nonincreasing returns to scale (NIRS) in their decomposition of model (6). Since there is clearly some uncertainty associated with the use of VRS in Malmquist indices, a decomposition model using CRS assumption was used in this study:

$$M_I^{t,t+1}(y^t, x^t, y^{t+1}, x^{t+1}) = EC_I^{t,t+1} \cdot TC_I^{t,t+1} =$$

$$\left[\frac{D_{I|CRS}^t(y^{t+1}, x^{t+1})}{D_{I|CRS}^t(y^t, x^t)}\right] \cdot \left[\frac{D_{I|CRS}^t(y^t, x^t) \cdot D_{I|CRS}^t(y^{t+1}, x^{t+1})}{D_{I|CRS}^{t+1}(y^t, x^t) \cdot D_{I|CRS}^{t+1}(y^{t+1}, x^{t+1})}\right]^{\frac{1}{2}} \qquad (9)$$

As shown by Försund (1997) simultaneous or inverse homotheticity must hold for the technology to ensure that Malmquist indices represent true total factor productivity (TFP). The first component (EC) in model (9) can be interpreted as a change in relative efficiency. Improvement in efficiency is indicated by an efficiency change score greater than one. The second term measures the shift in the technology frontier between two adjacent periods. A technical change score greater than one indicates progressive technological change, a score equal to one indicates no change and a score less than one regressive technological change.

VARIABLES AND DATA

Data

A panel data of 43 acute care hospitals in 1988 - 1994 (N = 43, T = 7) were used. The set of hospitals contained five university teaching hospitals and 38 other public hospitals, together producing approximately 93% of the total discharges in somatic hospital care in Finland. Private, military and psychiatric hospitals were excluded, along with psychiatric wards of acute hospitals.

The data were collected from hospital statistics published annually by the Association of Finnish Local Authorities and the National Discharge Registry. These were supplemented by research and teaching variables obtained via a separate questionnaire sent to the hospitals. The data were sent to the hospital administrations for final checking and verification. The final data set consists of seven output variables and four input variables (Table 1).

Inpatient and outpatient services

In the measurement of hospital patient output a crucial conceptual distinction is whether the output is the actual provision of the medical treatment itself or the resulting improvement in patients' health status assessed by QALYs for example, as discussed more thoroughly by Butler (1995). It could be misleading to use intermediate outputs, such as patient days, laboratory procedures or surgical operations, as measures of output in the cost function analysis. Perhaps the most successful approach for determining the final products of hospital inpatient care is the DRG classification system (Diagnostic Related Groups), which takes into account the hospital's case-mix. Although the DRG system has been evolving for several years, DRGs still suffer from certain weaknesses; it is considered a serious shortcoming that some of the DRGs exhibit significant heterogeneity in resource use because they do not explicitly take account of the severity of illness of the patient (Horn et al., 1985; Averill et al., 1992). However, the effect of this bias is difficult to clarify when the DRG system is used as a method for aggregating hospital inpatient treatments into a single output measure.

The Fin-DRG patient classification system, which is a Finnish version of the HCFA (Health Care Financing Administration) DRG grouping system (Virtanen et al., 1995), was used to weigh the inpatient output (ADMISSIONS). The DRG groups were weighted with actual average costs incurred by each episode. The DRG cost weights were based on a study using data from three Finnish university hospitals (Salonen et al., 1995). The variability in DRG groups was addressed by analyzing the outliers (measured by the length of stay) separately. If the inpatient episode exceeded a certain cut-off point, the remaining patient days were inserted into a separate variable (BED-DAYS). There have been claims that some hospitals attempt to artificially boost their output to increase their efficiency/productivity by splitting the individual's treatment episodes into several separate (re)admissions. This possibility was accounted for by deriving an additional measure of inpatient output (EPISODE), which uses supplementary clinical data (e.g. diagnosis, specialty, patient identification) to deflate a patient's separate admissions into a single output measure.

There is no widely accepted classification system or standard for outpatient visits. In addition, the introduction of short stay surgery has had a tremendous impact on the production of some elective operations. The altered balance between inpatient and outpatient care has led to some changes in data recording practices. Some hospitals have started to record some short stay surgery separately from the inpatient discharge register for outpatient visits. Thus it is possible that hospitals which record the relatively demanding short stay surgery as ordinary outpatient visits will appear inefficient. The hospitals were therefore asked if they recorded any of their short stay surgery as outpatient visits, and explicit weighting was used when necessary. In this study two outpatient visit classes were used: 1) outpatient visits (VISIT) and 2) emergency visits (EMVIS).

Teaching and research output

Teaching and research may increase the costs of hospitals both directly and indirectly. Direct costs are additional investments sunk in teaching and research programs, lecture rooms, research laboratories and equipment. An indirect influence of teaching and research is the loss of labor productivity in patient care: students and research projects absorb the time of the professional personnel; the more students in relation to professionals, the more time for teaching is needed.

Medical and nursing students are also production factors. Students are, by definition, less productive; they use more time, materials and tests for the same task as professionals, while salaries for postgraduate medical students are nearly as high as for professionals. Patients who take part in clinical research projects stay longer in hospital and use more outpatient visits, tests and treatments. It is also time-consuming to gather new medical knowledge from scientific articles or by attending seminars, training programs, meetings, development projects etc.

If productive efficiency is measured in terms of patient care alone, teaching hospitals perform poorly. However, in this study it was possible to describe the teaching and research outputs fairly accurately. As one measure of teaching activity the number of postgraduate medical students (RESIDENTS) was used. This variable can be interpreted as a one-year postgraduate training output. To measure the influence of nursing education the numbers of on-the-job training weeks of nursing students in the different hospitals (NURSE-EDU) were gathered.

Research output (RESEARCH) was measured by compiling the bibliographic data of refereed scientific articles and medical dissertations produced by all hospitals during 1988-1994. Each article was then weighted by the impact factor (SCI 1994) of the journal publishing it.

Input variables

Input variables used in this study fall into two categories: labour inputs and the use of materials and equipment (short-term capital investments such as various technical equipment located at operating theatres, CT-scan equipment etc.). The major long-term investments such as buildings are not included in the analysis since before 1993 these were paid by the state. Furthermore, due to the economic recession there was no significant activity in long-term investment at the hospitals in 1993-1994. It was possible to use two alternative measures to describe the material and short term capital inputs: the total costs of all non-labour inputs (MATCOST) and the number of staffed beds (BEDS)

Labour input variables were initially constructed by using the average full-time working hours in five employee categories: i) doctors, ii) nurses and other high-level care personnel, iii) care personnel with lower levels of education, iv) maintenance and catering personnel, and v) others (e.g. administrative staff). Because there was some variation in how the hospitals recorded their staff in the registers, we minimized this by combining the labour categories into two variables: one for doctors (DOCFTE) and one for other employees (OTHFTE).

METHODS AND SPECIFICATIONS OF THE MODELS

LP models (4) and (7) were used to calculate EC, TC and MI for four different models (Table 2). These specifications vary in the variables which are included in the input/output sets.

Table 2 here.

Using a full set of variables a high number of efficient observations is expected since the sample size is small (N=43). According to Smith (1997), the dangers of misspecification are most serious when simple models (small number of input/output variables) are used and sample sizes are small. Smith (1997) concluded that it will usually be modeller's advantage to erraneously include irrelevant variables than run the risk of excluding a potentially important variable from the model. In this study it was decided to use a relatively large set of input and output variables even though the sample size was rather small. To study the sensitivity of the results to variable selection, various model specifications were applied.

In DEA or econometric applications samples are often too small to guarantee asymptotic normality for time or firm means. This is especially true in applications where inefficiency distributions have truncated normal or exponential forms. If we can correctly define the data generating process (Simar, 1996) bootstrapping can be used to obtain approximate confidence intervals for a set of panel data efficiency indices $U = \{u_{it} | i = 1,...,N; t = 1,...,T\}$.

In this study we compare sample time (geometric) means for a random sample $\{MI_{it}\}_{i=1}^{N}$ of Malmquist indices given by (9): $\overline{MI}_t = \left(\prod_{i=1}^{N} MI_{it}\right)^{1/N}$, $t = 1,..,T$.

For each t we use the following steps in the bootstrap estimates of confidence intervals

1. Compute the sample time means $\overline{MI}_t = \left(\prod_{i=1}^{N} MI_{it}\right)^{1/N}$, $t = 1,..,T$

2. Compute small sample correction:

$$\ln(\tilde{MI}_{it}) = \ln(MI_{it}) \cdot \sqrt{\frac{N}{N-1}} + \ln(\overline{MI}_t) \cdot \left(1 - \sqrt{\frac{N}{N-1}}\right), \quad i = 1,\ldots,N, \; t = 1,\ldots,T.$$

3. Draw N times from the set $\{\tilde{MI}_{it}\}_{i=1}^{N}$ with replacement to obtain $\{\tilde{MI}*_{it}\}_{i=1}^{N}$

4. Calculate $\overline{MI}*_{i\cdot}(j) = N^{-1} \sum_{t=1}^{N} \ln(\tilde{MI}*_{it}(j)), \quad \forall\, i = 1\ldots N$

5. Repeat steps (3)-(4) J times (here J = 2 000) to obtain $\{\overline{MI}*_{i\cdot}(J)\}_{j=1}^{J}$.

The correction in step (2) is suggested by Atkinson and Wilson (1995) to avoid type-I errors in small samples. The values obtained can be sorted by algebraic value to construct confidence intervals via the bootstrap percentile method. In this study the bias corrected and accelerated (BC_a) method was used (Efron and Tibshirani, 1993).

When comparing firm means the contemporaneus correlation can be taken into account in the resampling process (Atkinson and Wilson, 1995). In this case, the step (3) should be modified to first draw from a set of time indices to obtain a set of resampled time indices which are used in the bootstrap process so that every firm uses the same time indices in jth replication.

RESULTS

The high correlation found between BEDS and MATCOST variables prompted the use BEDS as the proxy for non-labour inputs and the dropping of PMODEL3 and PMODEL4 from further analysis. The high correlation between the models using admission or episode-based inpatient output suggests that the suspected ‘output inflation’ due to artificial readmissions was not a problem. This was perhaps because hospitals were not reimbursed according to DRGs.

Table 3 shows the estimated annual average efficiency scores using the two models. The average technical efficiency was between 0.93 - 0.96 using PMODEL1 and between 0.84 - 0.91 using PMODEL2. Cutting down the number of output variables from seven to five had quite dramatic effect on the number of efficient observations. As indicated by the results in Table 3, there was a marked reduction in the number of efficient hospitals in several years.

Table 3 here.

The decompositions in Figures 1 and 2 show the development of hospital efficiency and productivity during the study period. Error bars formed by bootstrapping methods indicate 95% confidence intervals. Points above 1.0 indicate progress and below 1.0 regress. The two models used were broadly similar in terms of productivity development over the entire period (Figure 1). Changes in technology were larger and more variable than efficiency changes in all models. 1988-1989 was the only period to show significant decline in productivity in PMODEL1. Figure 1 also shows a positive development in technical efficiency in the 90's, except for the last year. A slight regress in efficiency was observed in 93/94, although in this case the effect on total productivity was offset by much greater progress in technology.

The analysis was completed by calculating correlation coefficients for each set of Malmquist decompositions for individual hospitals. The general impression is of a fairly high positive correlation between models PMODEL1 and PMODEL2, particularly for Malmquist indices (Spearman correlation 0.74).

Figure 1 here.

It seems that part of the productivity growth may have been due to new technologies allowing shorter inpatient stays. The average LOS has decreased from 8.7 in 1988 to 6.5 in 1994 and the long term bed-days have decreased 57 %. This has resulted in changes in hospital input mix which shows as an increase in the ratio of labour to beds. The use of labor inputs was stable while the number of beds decreased 16% in this period. However, this development was not significantly associated with productivity change. The most marked change in outputs was in the case of outpatient visits: the number of visits increased 22% in 1988-1994.

Table 4. here

The relationship between TC and changes in treatment practices, measured as the change in the ratio of treated patients in outpatient clinics to patients treated in inpatient wards ($\Delta_{t,t-1} VISITS / ADMISSIONS$) was tested using nonparametric Mann-Whitney statistics. No significant relationship was found over the period, suggesting that the productivity gains probably occurred neutrally since the outward shifts in the production possibilities did not concentrate into large or small outpatient/inpatient regions of the output space.

Hospital specific technical inefficiency seemed to be relatively invariant in time. Looking at consecutive years fairly high rank correlations in hospital specific technical efficiency scores were detected. In the basic model PMODEL1 which included all output and input variables the correlations ranged from 0.88 to 0.58. However, one exception was in 92/93 where the rank correlation was as low as 0.17. The corresponding correlations for the PMODEL2 were 0.92-0.64 and 0.35.

If it is assumed that technical inefficiency is invariant in time it is possible to construct confidence intervals for hospital means (Figure 2). The results show that for the majority of hospitals the confidence intervals are below 1.0 indicating a persistent technical inefficiency among these hospitals. There also seems to be more variation among the least efficient hospital which could mean that the time invariance of hospital efficiency does not hold for the most inefficient hospitals.

Figure 2 here.

There was some variation in the individual productivity indices, mainly due to the technology change component. However, only one out of 43 hospitals had a significantly negative productivity development over the period. Efficiency change seems to have played only a minor role in the overall productivity change. Further inspection of the individual efficiency scores and the components of the Malmquist index indicates that no individual hospitals were continuously efficient and simultaneously pushing the frontier outwards (TC over 1.0). This provides some evidence that there were no clear ‘technological leaders’ distinguishable in the sample, and that the diffusion of new cost efficient technologies perhaps occurs smoothly and quite randomly accross hospitals. It is often claimed that the diffusion of new medical technologies is faster in teaching and research intensive hospitals.

To formally test whether teaching or research activities within a hospital induced improvements in production technology, two measures were used: number of residents per doctor FTEs ($RESIDENTS_{t-1} / DOCFTE_{t-1}$) to decribe teaching intensity, and number of published articles per doctor FTEs ($RESEARCH_{t-1} / DOCFTE_{t-1}$) to describe research intensity. The null hypothesis tested was that hospitals located on the production frontier have the same teaching and research intensity compared to hospitals off the frontier.

The best-practice hospitals pushing the frontier outwards had significantly higher research intensity during 1988-1989, 1990-1991, 1992-1993 and 1993-1994 in PMODEL2 and during 1990-1991 and 1993-1994 in PMODEL1. The association with teaching intensity was not significant in either of the models.

The effect of state subsidy reform

Both the used models indicated a significant productivity increase during 92-93 and 93-94 according to the Malmquist indices. These results may reflect some of the effects of the provider-purchaser split in 1993. However, in addition to the new reimbursement system, there was another exogenous shock in the form of a relatively deep recession, in which the GDP % of health care expenditure surged from 7.5% to 9.3% during 1990-1992. The impact was visible in all of the figures, which show a clear widening of confidence intervals at the beginning of the recession. It also seemed to initiate a turning point in overall productivity development, which makes it more difficult to assess the progress due solely to the system renewal.

One possible way to study the impact of the reform is to monitor the hospitals' reactions to it. The change in the financing system prompted the hospitals to implement new management control systems such as management by objectives (MBO) or management by results (MBR). Secondly, some hospitals started preparations for output based reimbursement which in many cases meant calculating prices for various 'service packages'. The adopted new control systems often involved redistributing financial accountability to 'profit centers', which typically consisted of one or several clinics or operational units within the hospital. Cost accounting systems were developed and some hospitals started to use internal pricing for their intermediate products to facilitate a more accurate allocation of costs. As shown in Table 5 the adoption of new managerial control systems did not occur instantaneously. Some hospital districts, obviously in anticipation of the new reform, had started to experiment with the new managerial control systems already in 1991. In the end of 1994, two years after the state subsidy reform, only 10 of the 21 hospital districts used some form of a performance (output) based reimbursement. The rest of the hospital districts used per diem payment systems where predetermined prices for specific types of services, typically bed-days, were established. However, the payment systems were not usually stringent: financing surpluses and deficits could be settled in a political negotiation process between purchasers and providers. Losses were covered if the actual revenues fell short of the total operating costs and on the other hand hospitals were not permitted to retain all of the positive net revenues.

Table 5 here.

To investigate the impact of output based reimbursement on efficiency and productivity, a series of nonparametric Mann-Whitney tests was conducted. In a similar fashion, hospital group means were compared to explore the effect of new managerial systems to efficiency and productivity. The null hypothesis was that there were no differences in efficiency, efficiency change, technological change or productivity change between hospitals exploiting management control systems/output-based reimbursement and those that were not. Results are given in Table 6.

Table 6 here.

The results indicate that hospitals employing management control systems had significantly higher scores for TC, but not for EC or MI. Those hospital were already more efficient (significant at the 0.10 level) in 1992 before the implementation of any control systems. However, hospitals lacking managerial control systems outperformed other hospitals in productivity development in 93/94 due to larger increases in EC and TC.

Hospitals using output based reimbursement were also operating more efficiently initially. They also showed higher productivity scores but the differences were not statistically significant.

CONCLUSIONS

This study compared various model specifications in analysing the development of hospital productivity in Finland during a transition period towards ‘quasi-markets’ in health care. The use of non-parametric techniques and Malmquist productivity indices revealed significant productivity progress in the latter half of the observation period, mostly due to the exogenous rate of technical change. The state subsidy reform of 1993 may have accelerated the expansion of the production possibilities frontier, judged by the significantly higher technical change of hospitals during 1992 - 1993 and 1993 - 1994.

The findings also indicate that the choice of output selection did affect results to some extent. Although the reduced DEA model produced somewhat lower average efficiency scores and different Malmquist decompositions for the period of observation, there were moderate positive correlations between the individual efficiency scores generated by the models. Moreover, the main results on productivity development and frontier change were in good agreement accross the various model specifications.

The decomposition of the Malmquist index indicated a distinct increase of technical efficiency in 1992/1993, but also even in 1990/1991 when the country was initially hit by the economic depression. The Malmquist indices also demonstrate that there was an average annual productivity increase of 3-4%, mostly attributable to technological change. Since productivity was already improving well before the subsidy reform of 1993, the economic depression may have had a marked additional impact on hospital productivity growth.

Hospitals' direct responses to the new financing system were not markedly associated with increased efficiency or productivity. The state subsidy reform may have affected hospital performance through other mechanisms, e.g. increased political pressure, which could not be monitored in this study. According to the results using output based reimbursement did not lead to higher improvement in productivity than using per diem reimbursement. However, significantly higher rate of frontier change was found among hospitals employing managerial control systems in 92/93.

The effect of performance based reimbursement on hospital efficiency depends on whether hospitals accept the restrictions from the financing system as binding. In Finland hospitals have been relatively powerful and dominated the contracting game (partly due to the informational asymmetry) with the purchasers. Even after the reform of 1993, hospital budget deficits have been in many cases covered by the municipalities (purchasers). An interesting observation is that hospitals have continued to reduce average LOS by cutting down bed capacity even though the reimbursement was based on bed-days in most hospitals after the state subsidy reform. This might imply that revenue or profit maximisation are not likely to describe the behavioral objectives of public hospitals in Finland.

The initial purpose of Finnish 1993 subsidy reform was to distribute financial and decision-making power to municipalities rather than to create ‘internal markets’. However, the reform has been constantly compared in the health policy debate to the introduction of the NHS (National Health Service) internal market in the UK. Similar type of provider-purchaser split to the NHS reform has been introduced in the Swedish health care system (Tambour and Rehnberg 1997). Söderlund et al. (1997) examined the impact of NHS reforms on English hospital productivity using parametric methods. According to their study hospital productivity increased, but competition between hospitals had no significant effect on productivity during the first three years of the internal market.

Tambour and Rehnberg (1997) found higher technical efficiency in the group of hospitals with performance based reimbursement in their analysis of internal markets in Swedish health care. This result was supported by the empirical results from Gerdtham et al. (1999), which also indicated technical progress in the production frontier. Unfortunaly neither of the Swedish studies could account for differences in case-mix.

A system of fixed hospital grants was replaced by a combination of payment per case and a fixed grants in Norway (Magnussen and Solstad 1994). According to Magnussen and Solstad, the change of financing system did not have any substantial effect on hospital efficiency. All hospitals in their study seemed to improve cost efficiency regardless of how they were financed. However, as Magnussen and Solstad point out, their evidence is somewhat limited due to the small number of hospitals involved.

The results concerning the development in productivity seem to be consistent with the Scandinavian and British studies. Thus it may be possible to infer that the major driving force behind the observed productivity progress could be due to a source common to many European countries: new medical technology which allows shorter stays in hospitals. The impact of the internal market/financing systems on efficiency depends largely on the local solutions of implementing the reforms.

The empirical problem was disentangling the the effect of new organisational or managerial systems from the effects of new medical technology or other changes such as the economic depression. It is possible that the observed progress in productivity was due to combined effects. The economic depression may have tightened the financial constraints even more effectively than the new organisations of hospital financing and control.

There is a widely established belief (especially among health professional organisations) that the recession led to major cutbacks in hospital manpower, which in turn had serious consequences on patient care delivery. The present results contradict this popular view, showing that despite the (actually rather moderate) cuts in hospital resources and expenditure, hospitals were actually able to increase the delivery of services. Moreover, the DRG case-mix analysis reveals that hospitals were able to maintain the intensity of services at least at the same level as before.

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Table 1. Variable definitions.

	Variable name	Definition
Output variables		
Outpatient treatment:	EMVIS	Total number of emergency visits
	VISITS	Total sum of scheduled and follow-up visits
Inpatient treatment:	ADMISSIONS	DRG-weighted number of total admissions
	EPISODES	DRG-weighted number of total episodes
	BED-DAYS	Total number of bed-days exceeding the cutoff point defined in the outlier analysis
Teaching variables:	RESIDENTS	Number of residents receiving 1 year of training at the hospital
	NURSE-EDU	Total number of on-the-job training weeks of nurses
Research variable:	RESEARCH	Total number of impact-weighted scientific publications
Input variables	DOCFTE	Number of doctors in full time equivalents
	OTHFTE	Number of other staff in full time equivalents
	MATCOST	Total costs of material and equipment

BEDS	Total number of beds

Table 2. Model names and specifications

Name	OUTPUTS	INPUTS
Primal models		
PMODEL1	EMVIS,VISITS,ADMISSIONS,BED-DAYS,RESIDENTS,NURSE-EDU, RESEARCH	DOCFTE,OTHFTE,BEDS
PMODEL2	EMVIS,VISITS,ADMISSIONS,RESIDENTS,RESEARCH	DOCFTE,OTHFTE,BEDS
PMODEL1b	EMVIS,VISITS,ADMISSIONS,BED-DAYS,RESIDENTS,NURSE-EDU, RESEARCH	DOCFTE,OTHFTE,MATCOST
PMODEL2b	EMVIS,VISITS,ADMISSIONS,RESIDENTS, RESEARCH	DOCFTE,OTHFTE,MATCOST

Table 3. Average efficiency scores and the number of efficient observations

	1988	1989	1990	1991	1992	1993	1994
PMODEL1							
average efficiency	0.96	0.94	0.93	0.94	0.95	0.96	0.94
the number of efficient observations	21	20	17	17	20	22	23
PMODEL2							
average efficiency	0.91	0.89	0.84	0.87	0.88	0.91	0.87
the number of efficient observations	14	13	10	10	10	12	8

Table 4. Annual averages for the used outputs and inputs.

	1988	1989	1990	1991	1992	1993	1994	%-change
OUTPUTS								
EMVIS	16 923.6	16 805.9	16 269.4	16 336.3	16 635.1	16 120.2	16 764.7	-0.9
VISITS	54 819.1	54 356.0	54 386.8	51 788.6	55 477.1	63 322.3	66 743.9	21.8
ADMISSIONS	14 420.8	14 583.4	14 733.3	14 870.7	15 537.8	16 465.3	17 039.4	18.2
BED-DAYS	13 809.4	12 471.1	10 937.1	9 475.9	8 075.1	6 834.1	5 935.0	-57.0
RESEARCH	99.4	100.4	101.5	86.9	97.3	102.5	98.1	-1.4
RESIDENTS	24.4	25.1	25.6	25.7	23.1	20.6	22.7	-7.7
NURSE-EDU	1 753.4	1 624.8	1 561.1	2 263.5	2 349.5	2 617.6	2 348.2	33.9
INPUTS								
DOCFTE	82.0	84.0	84.9	83.4	81.7	84.3	85.5	4.2
OTHFTE	858.5	864.1	851.6	854.8	847.3	859.2	847.7	-1.3
BEDS	399.6	392.2	387.5	380.7	371.3	353.3	336.1	-15.9

Table 5. Average efficiency scores

	1988	1989	1990	1991	1992	1993	1994
The number of districts using management control systems (MBO, MBR)	-	-	-	2/ 21	4/ 21	10/ 21	13/ 21
The number of districts using some form of output based reimbursement	-	-	-	-	-	3/ 21	10/ 21

Table 6. Differences in group efficiency, EC, TC and MI means.

	Efficiency		EC		TC		MI	
	92	93	92/93	93/94	92/93	93/94	92/93	93/94
PMODEL1								
Diff. in mean (type1 -type2)	0.03	0.01	0.03	-0.02	0.05	-0.02	0.02	-0.03
p-value	p=0.085	n.s.	n.s	n.s	p=0.044	n.s.	n.s.	n.s.
Diff. in mean (type3 -type4)		0.03		0.02		0.02		0.03
p-value		p=0.042		n.s.		n.s.		n.s.
PMODEL2								
Diff. in mean (type1 -type2)	0.01	0.01	-0.01	0.02	0.04	-0.02	0.01	0.01
p-value	n.s.	n.s	n.s.	n.s.	p=0.010	n.s.	n.s.	n.s
Diff. in mean (type3 -type4)		0.01		0.02		0.01		0.03
p-value		n.s.		n.s.		n.s.		n.s.

type1 = Hospitals using management control systems

type2 = Hospitals not using management control systems

type3 = Hospital using output based reimbursement

type4 = Hospital not using output based reimbursement

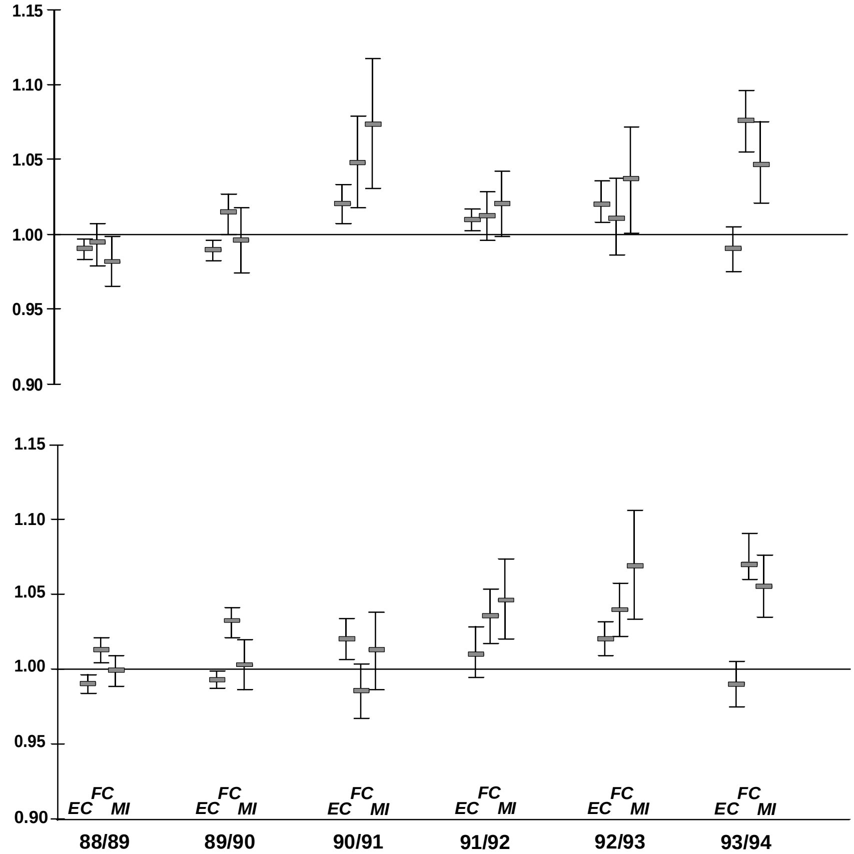

Figure 1. Malmquist indices (MI) and components FC and EC for PMODEL1 and PMODEL2. 95% confidence intervals estimated using the BC_a -method.

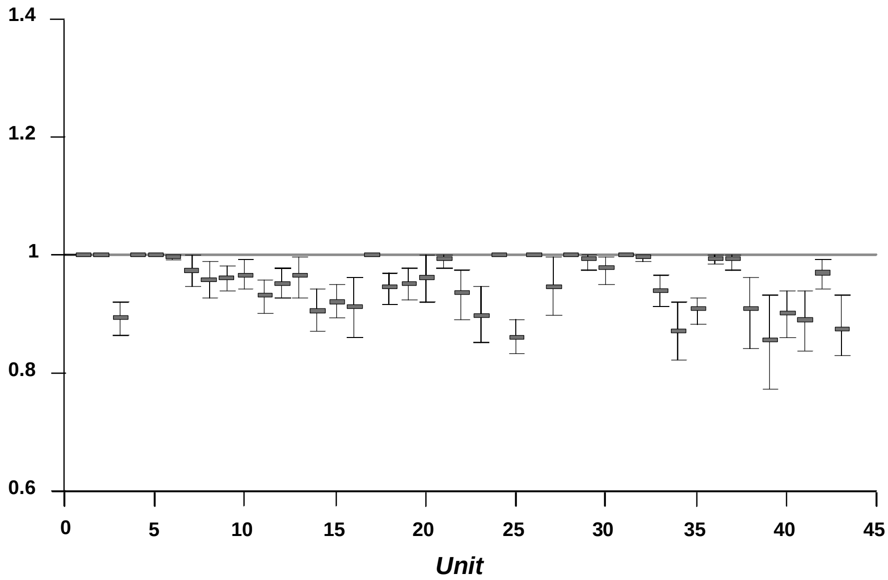

Figure 2. Confidence intervals for the hospitals specific technical efficiency scores.

95% confidence intervals estimated using the BC_a -method.